

## Characterization of Health Data using Neural Network and Routing in Health Monitoring



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### ABSTRACT

Use of Wireless Sensor Network in Health application has given rise to new area of wireless body sensor network. It can be used for timely monitoring of the health data, it helps to avoid happening of serious problems in case of the patients. There are different techniques which can be used to get the information about the health conditions of the patients. In this paper we propose a novel architecture for indoor hospital environments first the health data i.e. ECG signal is observed then classified as normal or abnormal and a new routing mechanism that helps to reduce network traffic load, energy consumption, and improves reliability of network.

**Key words :** Wireless Sensor Network (WSN), Wireless Body Sensor Network (WBSN), Electrocardiogram(ECG)

### 1. INTRODUCTION

It's become possible to do the health monitoring remotely because of the improvement in the microelectronic and radio technology. Since the growth of microelectronic technology it has become possible to have small sized sensors which can be used to collect the information from human body viz electrocardiogram (ECG) is used to find out the problems regarding the working of heart , Electromyography (EMG) is an electro diagnostic medicine technique for evaluating and recording the electrical activity produced by skeletal muscles. Electroencephalography (EEG) is an

Electro physiological monitoring method to record electrical activity of the brain. To do all these monitoring methods first we need to collect the data from human body by making use of different sensors the health data can be obtained and by using different methods the collected information can be classified according to the way of treatment or the type of disease. Many researchers have worked on the different technologies which can be used for the classification of the information collected from many patients. In this work the concentration is given to the ECG classification. Emerging back propagation NN algorithm is used to detect and characterize ECG.

Heart disease is the leading cause of death. In a particular situation the cardiac tissue are deprived of oxygen. If the deprivation continues for extended periods of time, the cardiac tissue will begin to die. This tissue death is called infarction and is one of several conditions commonly known as a heart attack. Tissue that has died is no longer functional and weakens the mechanical pumping function of the heart [1, 2].

Several possible methods have been proposed, which take recorded cardiac electrical signals for observation, but these methods generally have low accuracies and report too many false alarms to be clinically practical.

This work presents a new approach for analyzing a cardiac patient condition using recordings of the electrical signals occurring in the heart. This approach is beneficial because the required recordings can be obtained without any invasive medical procedures.

### 2. CARDIAC SYSTEM.

The cardiac muscle (heart) is the center of the cardiovascular system. This muscle pumps life-sustaining blood to the entire body. The blood supplies oxygen and nutrients to the body's organs so that they can perform their designated functions. The

heart is controlled by a very precise electrical system. This system regulates the mechanical pumping action of the heart so that the entire cardiovascular system can function properly. If a problem occurs in the electrical system of the heart, it can have devastating effects for the entire body.

**2.1 Cardiac Function**

The function of the cardiovascular system is to supply oxygen to the organs of the body. Blood is the body’s medium for transporting oxygen to the organs. The muscular pump, known as the heart, pumps blood throughout the body. A complex set of arteries, veins and capillaries connect the heart to the entire body.

The mechanical pumping action of the heart results from electrical activation fronts traversing the cardiac tissue. Figure 1 shows an example of the electrical signal, also known as the electrocardiogram (ECG), for a single heartbeat. The labels indicate the approximate location of the important waves and components of the ECG Signal.

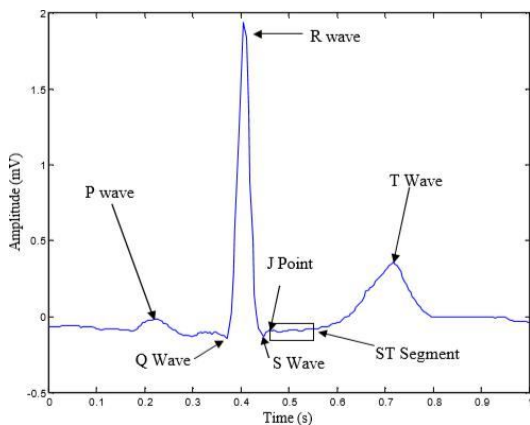


Figure 1 – Electrical signal (ECG) with important wave components labeled.

The heart tissue experiences a series of stages of electrical depolarization and repolarization that lead to particular muscle contractions. These stages, summarized in Table 1.1.

SI NO	Electrical Function	Mechanical Function	Electrical Representation
1	SA Node emits electrical pulse		
2	Atria	Atria	Start of P

	depolarize	contract	Wave
3	Electric pulse pauses at AV Node	Blood flows to ventricles	End of P Wave
4	Pulse travels down His Bundle to Bundle Branches		Q wave
5	Atria repolarize while ventricles depolarize	Atria relax, Ventricles contract pumping blood to lungs and body	R and S Wave
6	Ventricles repolarize	Ventricles relax	T Wave

Table 1.1 - Stages of cardiac excitation with corresponding ECG representation.

**3. PROPOSED METHEDODOLOGY.**

The electrocardiogram (ECG) plays an important role in the process of monitoring and preventing heart attacks. In the last decade many approaches to QRS detection have been proposed, involving artificial neural networks, real time approaches, genetic algorithms, and heuristic methods based on nonlinear transforms and filter banks .In figure 1 describe the ECG signals P interval-QRS interval and T interval detection of interval in ECG signal is more complex. Purposely QRS wave is used to detect arrhythmias and identify problems in regularity of heart rate. These waves correspond to the far field induced by specific electrical phenomena on the cardiac surface, namely, the atrial depolarization, P, the ventricular depolarization, QRS complex, and the ventricular repolarization, T. Sometimes, in an ECG signal, QRS complexes may not always be the significant waves because they change their structure with respect to time for different

Biradar Shilpa *et al.*, International Journal of Computing, Communications and Networking, 7(2) April - June 2018, 270-277 conditions, so that consider always be the strongest signal interval in an ECG signal. In order to address this problem, the analysis of ECG signals for detection of electrocardiographic changes have been carried out using techniques such as autocorrelation function, time frequency analysis, wavelet transform (WT) and neural network [3].

The identification of QRS complex is tough task because P or T wave have similar wavelet transform based QRS complex detector using dyadic wavelet transform, as QRS and ECG signal can be affected and degraded by other sources such as noise. Wandering due to respiration, patient movement, interference of the input power supply, contraction and twitching of the muscles and weak contract of ECG electrodes. Therefore, it is essential for the QRS detector to avoid the noise. The QRS region is a structure on the ECG that corresponds to the depolarization of the ventricles. Because the ventricles contain more muscles than the atria, the QRS region is larger than the P wave. Therefore QRS detectors must be invariant to different noise sources and should be able to detect QRS region even when the morphology of the ECG signal is varying with respect to time. The each sample of QRS region passed through wavelet transform based QRS region detector using Dyadic wavelet transform algorithm.

The ECG signal has to be processed using wavelet transform method to characterize the ECG data and classify using networks architectures [5]. Application of wavelet transforms principal component analysis (PCA) and neural network structures in order to detect and classify different kinds of heart arrhythmias. In the proposed system, emerging neural network structures used in order to find the for the classification of specific types of ECG signal have been compared. A neural network classifier to detect and classify the ECG signal. They also used PCA as a method to select and extract features from the ECG signal used different types of multilayer neural network as a classifier to detect two types of ECG patterns. ECG beat classifier performance by using a combination of dyadic wavelet transform (DyWT) and principal component analysis (PCA) [6] in order to prepare a more effective input data for neural network classifier, leading to better classification results. Principal components analysis (PCA) is a well-established technique for feature extraction and

dimensionality reduction and has been used in a wide range of ECG signal analysis [4]. Dyadic wavelet transform (DyWT) is a time frequency analysis method which differs from the more traditional short time Fourier transform (STFT) by having a variable window width. Back Propagation Neural network detects and classify the effective input data provided by PCA and DyWT.

The schematic block diagram of the proposed system for the ECG beats classification as shown in figure 4. The first stage is pre-processing stage including four levels of data processing which are signal filtering, sample selection, feature extraction, and finally dimensionality reduction. The other stages are main process and classification of ECG beats.

### 1) PRE-PROCESSING STAGE

In this pre-processing stage a method of signal filtering presented and applied to remove noise. A raw ECG signal, which has been degraded by other sources such as wandering due to respiration. It is obvious that the noise has been removed, leading to a better performance of the neural classifier. Filter design use integer coefficients resulting in faster computation. Time scale representation of signal obtained using digital filtering techniques. Resolution of signal is changed by filtering operation.

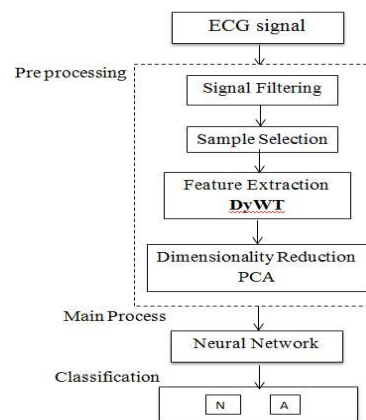


Figure 2. Block diagram of ECG signal classification

### 2) Main Process

Neural network input is most important component of designing neural network based pattern classification; since even the best classifier will perform poorly if the input is not selected well.

Neural network consists of single layer of neurons where output of each neuron is given as input to all other neurons.

### 3) Classification

Neural Network is a powerful pattern recognition tool. It is defined as software algorithms that can be trained to learn the relationships that exist between input and output data, including nonlinear relationships. In this back propagation neural network algorithms is used to detect and characterize ECG signal. A back propagation neural network consists of at least three layers (multi-layer perception) an input layer, at least one intermediate hidden layer, and an output layer. Typically, input units are connected in a feed-forward fashion with input units fully connected to units in the hidden layer and hidden units fully connected to units in the output layer. An input pattern is propagated forward to the output units all the way through the intervening input-to-hidden and hidden to- output weights when a Back Propagation neural network(BPNN) is cycled. Feed-Forward Neural Network (FFNN) is used to classify different ECG signals.

## 4. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are used for obtaining information from complex or inaccurate data as well as they are involved in pattern extraction and detection of processes that are not recognized either by human or computer.

Neural Networks (NN) are highly interconnected and simple processing units which is designed to model the way human brain performs a particular task. Each unit is called a neuron. It forms a weighted sum of its inputs and a constant term called bias is added. This sum is passed through a transfer function such as linear, sigmoid or hyperbolic tangent. In the construction of neural architecture, the choice of number of hidden layers and the number of neurons in each layer is one of the most critical problems/ In order to find the optimal network architecture, several combinations should be evaluated. These combinations include networks with different number of hidden layers, different number of units in each layer and different types of transfer functions as shown in figure 3

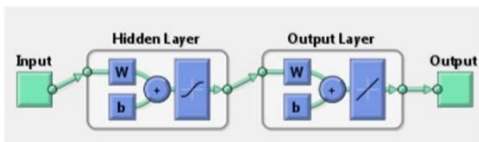


Figure 3 Neural network

### Architecture

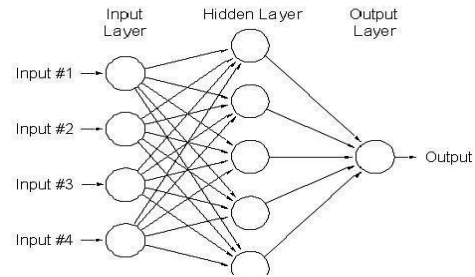


Figure 4 simple neuron architecture

It is made up from an input, output and one or more hidden layers. Each node from input layer is connected to a node from hidden layer and every node from hidden layer is connected to a node in output layer as shown in figure 4. There is usually some weight associated with every connection. Input layer represents the raw information that is fed into the network. This part of network is never changing its values. Every single input to the network is duplicated and send down to the nodes in hidden layer. Hidden layer accepts data value, this new value is then send to the output layer but it will also be modified by some weight value, this new value is then send to the output layer but it will also be modified by some weight from connection between hidden and output layer. Output process information received from the hidden layer and produces an output. This output is then processed by activation function.

### Back Propagation (BP) Algorithm

One of the most popular NN algorithm is back propagation algorithm. BP algorithm could be broken down to four main steps. After choosing the weights of the network randomly, the back propagation algorithm is used to compute the necessary corrections. The algorithm can be decomposed in the following four steps:

- Feed-forward computation
- Back propagation to the output layer
- Back propagation to the hidden layer
- Weight updates

The algorithm is stopped when the value of the error function has become sufficiently small.

## 5. PROPOSED ROUTING PROTOCOL

In this paper, a Routing Protocol is proposed that can increase the survivability of nodes as well as network by avoiding nodes with low residual battery. To achieve this aim, a cost metric that optimizes energy utilization in the network has been developed. The concept of drain rate has also been incorporated in the cost metric to capture the effect of current load on the node. A realistic battery model is assumed to characterize the recovery effect observed in the batteries.

**Battery Model**

In traditional routing protocols, the battery is assumed to have linear charge and discharge characteristics. On the other hand, real battery drains more rapidly when higher loads are applied. The life span of a battery and its delivered power mainly depend on the current discharge profile [7]. If the discharge current magnitude in a battery is higher than its rated current capacity, it supplies smaller amount of energy. This effect is termed as “rate capacity effect” which results from the fact that at a higher discharge rate, electrochemical reductions occur only at the outer surface of the cathode. This implies that a battery can deliver more energy if the rate of current drawn is lower. The lifetime of a battery can also be increased by the alternating incidences of idle and discharge phases. During the idle periods, the battery partially recovers its lost capacity. This consequence is known as “recovery effect” [7]. It is a phenomenon that the charge recovery rate is higher initially but tapers off with time. A simple instinctive function as in equation (1) is used here to empirically capture the recovery effect in the battery model as suggested by [8]

$$r(t) = C_1 e^{-c_2 t} \tag{1}$$

where  $c_1$  and  $c_2$  are constants,  $t$  is time, and  $r(t)$  is the recharge rate of the battery. It is assumed that the battery recharges at a rate of  $d(t, v(t))$  when in use, and recharges at a rate of  $r(t, v(t))$  when at rest, where  $v(t)$  is the voltage of the battery at time  $t$ . In general, different batteries have different functions of  $r(t)$  and  $d(t)$ . The values of constants  $c_1$  and  $c_2$  depend upon the type of battery technology used. However, it is assumed that the discharge rate remains constant, i.e.  $d(t, v(t)) = c_3$ , for the simulation, as the discharge relies on the size of the

packet being transmitted and not on current voltage and past usage.

**Route Selection**

Cost Metric Every node, except the destination node, estimates its cost,  $C_i$ , by the equation below

$$C_i(t) = P \left( \frac{F_i}{R_i(t)} \right) DR_i \tag{2}$$

where  $P$  is the power consumed in transmitting a packet,  $F_i$  is the full battery capacity of node  $i$ ,  $DR_i$  is the drain rate of node  $i$  calculated by exponential weighted moving average method [11].  $R_i(t)$  is the residual battery capacity of the node  $i$  at time  $t$ , and is given by:

$$R_i(t) = R_i(t - t_i) + \text{charge recovered in time } t_i \tag{3}$$

where  $t_i$  is the idle time. This cost metric assists in discovering the links with the least cost nodes, so that data packets can shun the nodes with quick depleting batteries. The cost given by this metric is directly proportional to the power consumed in routing a packet in a node, and inversely proportional to the normalized residual battery capacities of these nodes. Therefore, nodes with higher traffic densities are spared during routing. These are the three basic operations in this routing protocol: route discovery, data routing, and route maintenance, among which route discovery is described in the following sections.

**Route Discovery**

In this it is a reactive routing protocol that can construct the route when data transmission is required. In this protocol, a source node broadcasts the Route Request (RREQ) packet to the entire network, and all the nodes rebroadcast the received RREQ packet immediately. When a source device transmits data to a destination device whose route is unknown, it relays an RREQ along with its coordinates to its neighbors. It also assigns sequence numbers to this RREQ packet so as to differentiate between accomplished and new sessions. The intermediate nodes that have residual energy greater than the threshold ( $R_{th}$ ) retransmit this packet. This threshold ( $R_{th}$ ) is decreased with the progress of time to ensure that all nodes have their residual battery

charge at the same level. The destination, on receiving an RREQ packet, adds that to its route reply list and broadcasts a Route Reply (RREP) packet. The intermediate nodes act as cooperative nodes and forward these RREP packets towards the source only when their residual energy is greater than the threshold ( $R_{th}$ ). The following distance condition is satisfied; otherwise, the nodes become selfish nodes and the RREP packets are dropped:

$$d(N_i, N_s) \leq d(N_j, N_s) \quad (4)$$

$$d(N_i, N_d) \geq d(N_j, N_d) \quad (5)$$

where  $(N_i, N_j)$  is the distance between the pairs of nodes  $N_i$  and  $N_j$ ; and  $N_i, N_j, N_s$  and  $N_d$  are the current, previous hop, source, and destination nodes, respectively. In this routing protocol, each node is involved in route construction in accordance with the remaining battery capacity. Each node adjusts the retransmit timing of the RREQ packet since the RREQ packet that arrives first is used to construct the route. The retransmit timing is determined by the remaining battery capacity. Therefore, when the node accepts the RREQ packet from a new node, it initiates the timer for the retransmit of the received RREQ packet by verifying the residual battery capacity. The timer period is fixed to a large value when the battery capacity is small. Conversely, it is fixed to a small value when the battery capacity is large. The destination, on receiving an RREQ packet, adds that to its route reply list and broadcasts the RREP so that all the intermediate nodes can use this information to check the distance condition. Intermediate nodes forward these RREP packets towards the source only when their residual energy is greater than the threshold value; otherwise the RREP packets are dropped.

## 6 RESULTS

ECG Signal .

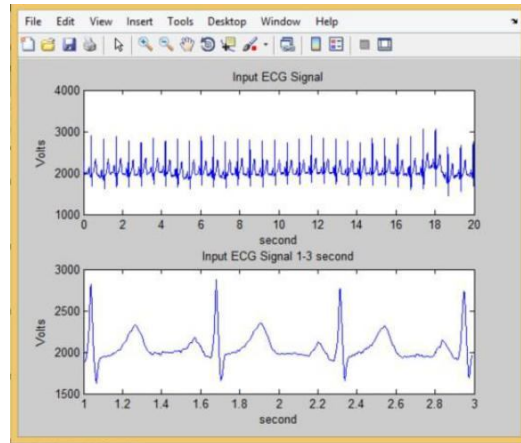


Figure 5: Input ECG signal

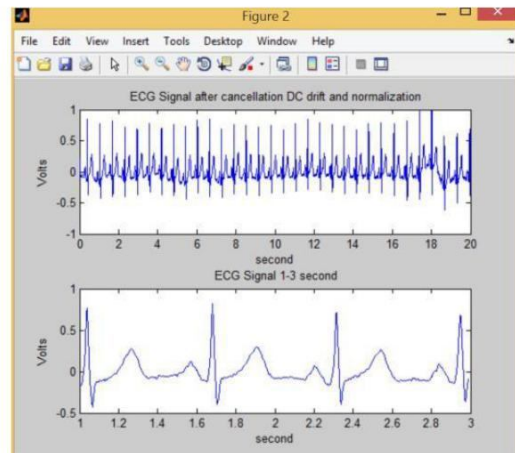


Figure 6 : ECG after DC Drift cancellation and normalization

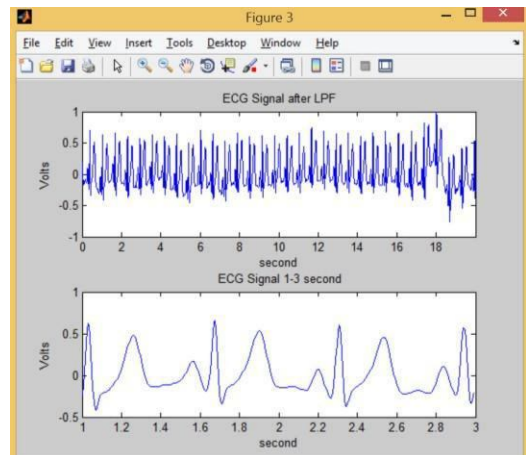


Figure 7. ECG signal after LPF

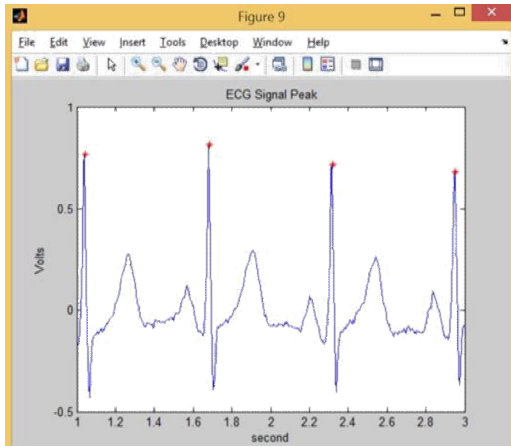


Figure 8 . ECG signal peak

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Columns 29 through 32
    3574    3703    3833    3962
HEART RATE IS:::
98
R-R Interval is less than 0.6Sec(120 beats per min), Suffering from Tachyocardia
! >>
    
```

Routing:

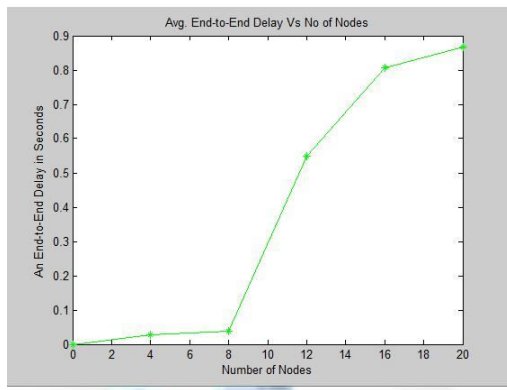


Figure 9 Average end-to-end delay

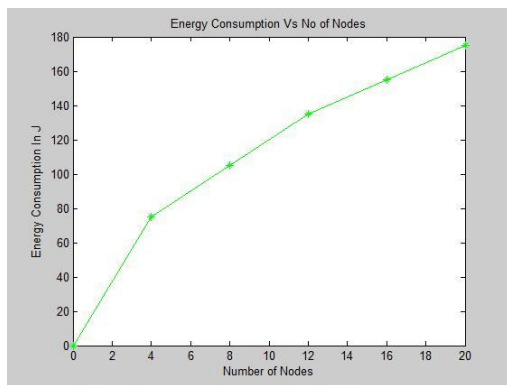


Figure 10. Energy Consumption

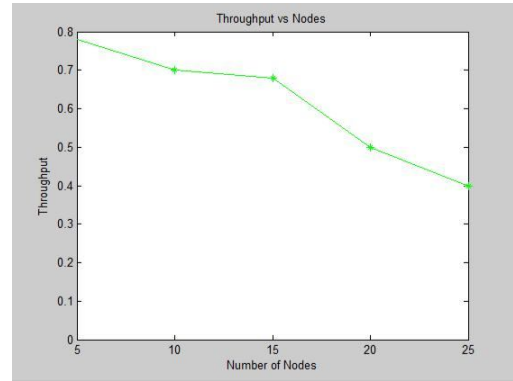


Figure11. Throughput

### CONCLUSION

The ECG signal can be classified more accurately and efficiently using neural network based technique. Once the signal classification is done it can be sent correctly with no delay to the destination using the described protocol and the overall system will help in providing good service to the human being life monitoring system.

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