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Full Length Research Paper

Power line enhancement for data monitoring of neural electrical activity in the human body

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Distance and real-time data monitoring are the necessary condition that makes any system in good working order. Recent advancements in micro-electronics and wireless technology enable the application of wireless sensors in both industry and wild environments. However, Long-distance wireless communication has several drawbacks like limited bandwidth, considerable costs and unstable connection quality. Therefore, Power Line Communication (PLC) using pre-established Power Lines (PL) becomes more attractive for high data transmission technology. This paper reviews the existing distance data monitoring systems and presents a case study for data transferring of temperature and heart beat measurement. The simulations were carried out on the detected and transmitted signals of medical data using Matlab program. Furthermore, a framework of Intelligent Neural Monitoring System (INMS) is proposed for future works. The performance of PLC as a channel to transfer the patient Heart Rate (HR) is evaluated based on the Bit Error Rate (BER).

Key words: Power line communication, electrical signals, data monitoring, electrocardiogram, electromyogram, neural interfacing.

INTRODUCTION

Data Monitoring of Human Electrical Activity is a branch of Body Sensor Networks (BSN) converged with wearable computing technologies to sense many kinds of vital signs in the human body detected by electro-cardiogram (ECG) and electromyogram (EMG) and accelerometer sensors (Dongheui et al., 2007).

Systems extracting temporal parameters have mostly used cameras or marker-based approaches to extract limb positions and orientations. Currently, BSN employs a variety of sensors and the most common are accelerometers and gyroscopes because of their small size, low power usage, and useful motion data (Eric et al., 2009).

Monitoring various signals from human body is presently an active area of research and development. Increasingly, monitoring devices are becoming wireless to allow patient mobility. Another trend is to connect monitoring devices into a network using wireless sensor nodes (Behcet et al., 2006). The close connection with its immediate physical environment allows sensors to provide localized measurements and detailed information which is hard to be obtained traditional manual measuring approaches. Two of the most important technologies that have emerged in these years are Radio Frequency Identification (RFID) and Wireless Sensor Networks (WSN) (Ze et al., 2008).

Recently, there is an increasing demand for long term continuous monitoring of biosignals. Telemedicine and healthcare are fast-growing issues which require new innovative ideas to successfully position new reliable products (Madjid, 2009). In order to provide a truly pervasive monitoring and sensing environment, a number of research issues have to be addressed. These include biosensor design, biocompatibility, wireless communication, power management, and autonomic sensing. The ubiquitous computing abilities of BSN offer the prospect of continuous monitoring of human health in any environment (home, hospital, outdoors or the workplace). In the past few years, RFID and WSN have been separately studied. Nowadays, wearable solutions

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for mobile computing and health monitoring system receive much attention, and wireless communication with integrated sensors has been adopted in daily healthcare monitoring system. Particularly, wearable inductor becomes a strong candidate for inductive coupling in wearable applications of less than 1cm distance. However, they suffer from static and dynamic variations during manufacturing process and operation (Seulki et al., 2009). Wireless technologies developed for wireless personal area networks (WPANs), such as Bluetooth and Zigbee, have been investigated to interconnect biomedical sensors within the body area (Shu-Di et al., 2006).

The integration of data from disparate sources improves the clinical decision-making process, especially in clinical situations such as the emergency room. If the clinical test results can be gathered and shared immediately, it will immensely improve the response time (Wee et al., 2009).

Here, time delay in patient care represents a critical issue, and it is important to monitor the surgical competency which is becoming a major public concern in light of recent major surgical errors in Europe and the U.S. (Rachel et al., 2009).

The major objective of modern health care is to ensure that patients are treated in a community setting and supported at home when ever possible. Therefore, the main motivation in the clinical requirement is to obtain activity profiles of patients using a minimal number of sensors without affecting the patient's behavior or daily routine (Louis et al., 2009). Typically, in-home monitoring systems a variety of vital signals such as heart rate, blood pressure, oxygen saturation, body weight and temperature are usually sent via phone lines to a central monitoring unit where a health professional reviews the information and responds appropriately. There is no cost-effective in such type of monitoring system, and thus, most monitoring companies rely on phone lines (He, 2008).

The Wireless Body Area Networks (WBAN) is network whose nodes are usually placed close to the body on or in everyday clothing. To successfully deploy body area networks that can perform long-term and continuous healthcare monitoring, it is critical that the wearable devices be small and lightweight (Shuo et al., 2009). The significant advance in remote monitoring is the integration of the active sensor nodes which are considered for a variety of applications due to the low-cost, low-power, and multifunctional aspects (Patricia, 2007).

Another application of wireless communication for data monitoring system is the Global Positioning System (GPS) technology. GPS can provide position information with accuracy to a few millimeters in near real-time. It is widely used in navigation and has become an established technique in geodesy (Knecht and Manetti, 2001; (Gethin et al., 2003).To allow unlimited subject's mobility, long-distance wireless communication is used such as General Packet Radio Service (GPRS) (Piotr, 2010).

The recent movement toward intelligent micro grids and the continued pressure on utility companies to provide a more reliable service to customers have amplified the importance of robust, real time communication between remote points of the network and the control room. One way to achieve this is the use of the existing power line infrastructure as the communications medium, a process generally known as PLC (Robson et al., 2010). AC Power Line Communication technology is being used in many applications for example (Adnan et al., 2009) low rate of transfer of data in smart home, automation system, remote metering for electricity billing and light controlling system. PL for data communication offers several advantages: 1) Total cost of new installation of PLC system result in saving cost of new wires and labour charges. 2) Availability of PL outlet/ socket makes PLC technology flexible. 3) Regarding industrial uses, because of place and environment limitations imposed by the infrastructure of factories and power plant, new installation of extra wiring for monitoring purposes present several difficulties.

Communication in a PL network must occur at three levels – high voltage (HV), medium voltage (MV) and low voltage (LV). The HV network consists of strategically positioned major substations within the supply region. The MV network consists of many distributor substations that are linked to the major HV substations via branched networks or underground or overhead MV cable. Residential consumers are connected to the LV network and no communication infrastructure exists at this level (Poobalan and Sunil, 2006).

Presently, the demand for broadband internet service is increasing dramatically. However, these services are usually given to urban areas since building cost of communication networks is very high, thus, the services are not profitable in rural areas. Due to the aforementioned reasons of the high cost establishment, a PLC using pre-established PL becomes more attractive for high data rate internet and Voice over Internet Protocol (VoIP) services (Jae-Jo et al., 2005; Lin et al., 2009; Yu and Zhaoyu, 2009; Qi-Song and Xiao-Wei, 2008). Similarly, PLC can also be used to transfer the medical data of the patients to the doctor, such that the doctors can view transferred data and give their comments.

Brain Computer Interface is one of hopeful interface technologies between human and machine. However, brain waves are very weak and there exist many kind of noise due to the distance of data transferring (Kenji and Kiyoto, 2006). The conventional methods used for distance data monitoring of neural electrical activity changes rely on detecting the presence of particular signal features by a human observer. Due to large number of patients in intensive care units and the need for continuous observation of such conditions, several techniques for automated data monitoring and analyzing

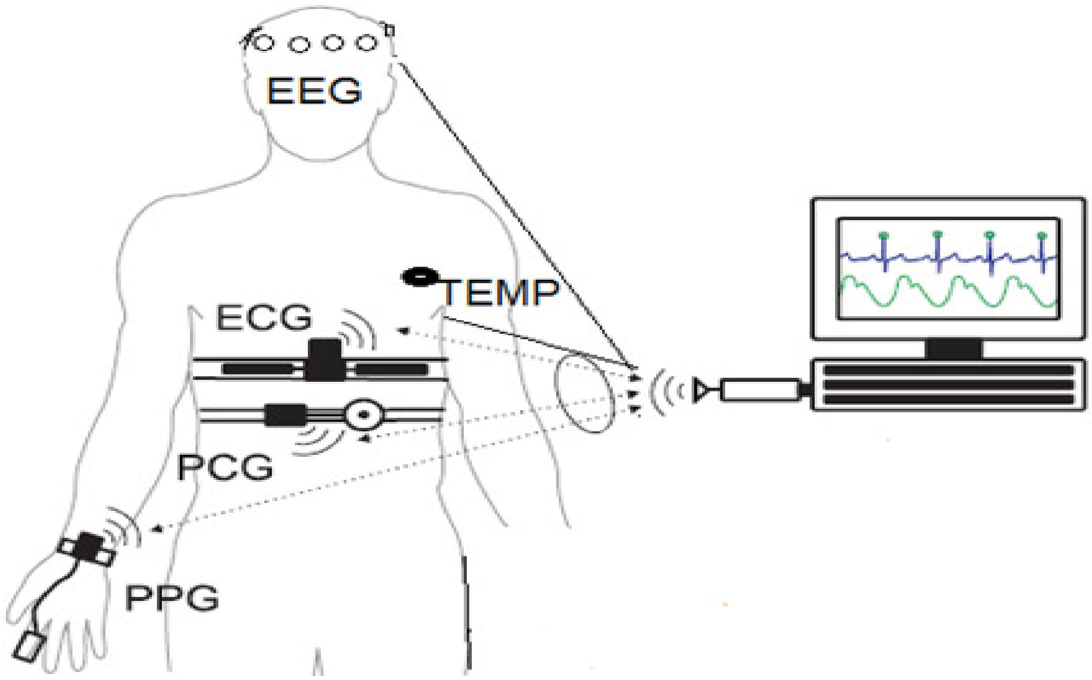

Figure 1. System architecture of the detected signals.

have been developed, the application of adaptive neuro-fuzzy inference system has been proposed for classification of ECG signals (Elif, 2009). Neural network analysis on heart rate variability data was used to assess driver fatigue (Patel et al., 2011). Numerous approaches derived from the theory of signal analysis have been implemented to obtain representations and extract the features of interest for classification purposes (Ling et al., 2009).

In this paper, a simulation study of data transmission over PLC based on Orthogonal Frequency Division Multiplexing (OFDM) technique has been carried out using Matlab program. A wireless communication system for medical data transferring is tested and the preliminary results are presented. In addition, a developed programming model is utilized to simulate the electrical activity of human body signals.

Body's electrical signals

Bioelectric signals result from the electrical response of physiological systems and the sources of these signals are transient changes. In particular, bioelectric signals arise from the time-varying transmembrane potentials seen in nerve cells (neuron action potentials and generator potentials) and in muscle cells, including the heart (Robert, 2004).

Therefore, before describing and analyzing the required electronic circuits covering the main components such as amplifiers and filters to improve the signals, it is appropriate to describe the sources and properties of these signals (That is, their bandwidths, distribution of amplitudes, and noisiness). Generally, the biomedical signals can be subdivided into two major classes (Volmer and Orglmeister, 2008).

Endogenous signals

These signals are arising from natural physiological processes and measured within or on living creatures using the following indicators: 1) Electroencephalogram (EEG); 2) Respiratory rate; 3) Temperature; and 4) Blood glucose. The system architecture of the body sensor network with coordinator of such signals is depicted in Figure 1.

Exogenous signals

These signals are applied from without (generally noninvasively) to measure internal structures and parameters. Electrical impulses from the heart muscle cause the heart to beat. The impulse is an electrical signal begins in the sinoatrial node (SA), located at the top of the right atrium. While an electrical impulse is released from SA, it causes the atria to contract. The signal then passes through the atrioventricular (AV) node. The AV node verifies the signal and sends it through the muscle fibers of the ventricles, causing them to contract. The SA node sends electrical impulses at a certain rate, but the heart rate may still change depending on physical

Table 1. Normal amplitude and time period values for ECG parameters.

Amplitude		Duration	
Wave	**Signal voltage (mV)**	**Wave**	**Time (sec)**
P – Depolarization of atria	0.25	P-R Delay of AV node to allow filling of Ventricles	0.12 –0.20
R – Contraction of ventricles	1.60	Q-S Depolarization of ventricles	0.35 – 0.44
Q – Depolarization of ventricles	0.4	S-T Beginning of ventricle repolarization	0.05 – 0.15
T – Ventricular repolarization	0.1 - 0.5	P- Depolarization of atria	0.11

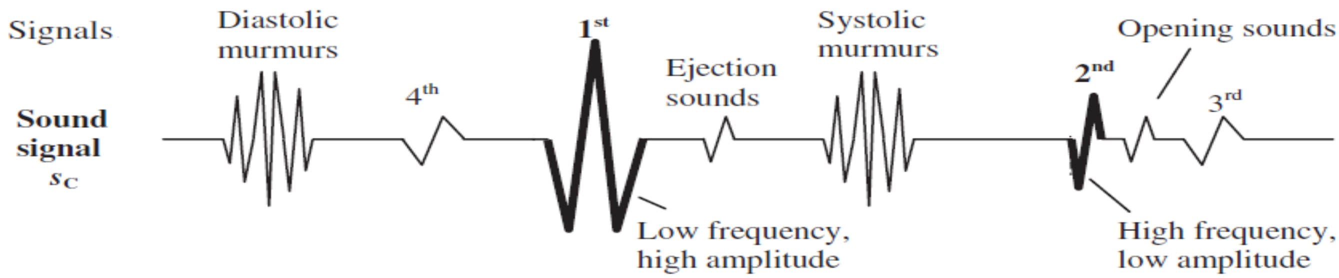

Figure 2. The graphical representation of the heart sounds signals.

demands, stress, or hormonal factors. The ECG wave contains information about the electric rhythm, electric conduction, muscular mass, presence of arrhythmia (irregular heart beat), ischemia (lack of blood flow) and infraction. A typical amplitude and duration of ECG wave are illustrated in Table 1. The graphical representation of sounds produced by the heart beating and flow of the blood are shown in Figure 2. The first heart sound (S1) is produced due to the closure of atrioventricular valves. It is loudest and the longest of all the heart sounds and its duration is about 140ms. It consists of vibrations of low frequencies and the frequencies range from 10 Hz to 200 Hz. The second heart sound (S2) is produced due to the closing of the aortic and pulmonary valves. It is of shorter duration (110ms) and consists of two high frequency components. The third heart sound (S3) is mainly caused due to the rapid filling of the ventricles during early diastole. The fourth heart sound (S4) is produced due to the late diastolic filling after the contraction of the atria (Eugenijus, 2011; Abbas and Rasha, 2009).

The human brain is a complicated system, and exhibits rich spatiotemporal dynamics. EEG is one of the most important tools among amounts of techniques probing brain activity. It is especially useful in diagnosis of neurological diseases (Rosso et al., 2004; Hazarika et al., 1997). The electrical signals of the brain can be measured by means of brain cells activity using EEG Electrodes on the scalp. The different waveforms with their frequency and voltage generated by the brain are illustrated in Table 2. Low amplitude beta with multiple and varying frequencies is often associated with active, busy or anxious thinking and active concentration (Ling et al., 2009). Other signal of human body is generated by the body temperature in many ways like a machine. Every time the human body does work of any sort, heat is generated, in much the same way as heat is generated in machines by friction. The variation of the actual output signal due the change in temperature is the indication of the body condition.

System modelling of power line channel

The high frequency signal of power line channel is mainly interfered by various additive noises. Such noises are presented in the block diagram as seen in Figure 3. The high frequency interference environments of PL can be divided into the following types of noise (Zimmermann and Dostert, 2002; Ma et al., 2010):

1. Colored background noise;
2. Narrow band noise
3. Periodic impulse noise synchronous with power frequency
4. Non-periodic impulse noise
5. Burst noise
6. Additive white Gaussian noise

The simulated model of PLC is illustrated in Figure 3 and the frequency response of the multipath PLC is given by (Zimmermann and Dostert, 2002).

$$H(f) = \sum_{i=1}^{N} g_i A(f, d_i) e^{-j2\pi f \tau_i} \tag{1}$$

Table 2. Normal values for EEG parameters and its waveforms.

Wave		Frequency (Hz)	Voltage (µV)	Subject condition
Generated	Pattern			
Beta		14 – 30	10 – 20	Activity, thinking
Alpha		8 – 13	Kids – 75 Adult – 50	Relax, closed eye
Theta		4 – 7	Kids – 50 Adult – 10	Light sleep, emotional stress
Delta		0.5 – 3	10 mV	Profound sleep

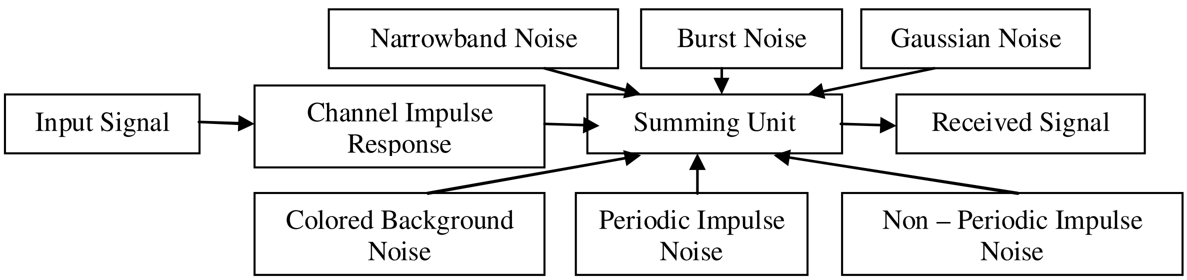

Figure 3. Simulated model of power line channel.

Where, i - number of the path (for short delay $i = 1$); τ_i - delay of a path; d_i - length of path i; g_i - weighting factor for path.

The transmission of data on PLC is achieved by using OFDM. This technology is transmitting multiple signals simultaneously over a single transmission path, such as a cable or wireless system. It offers resistance against multipath, burst noise, frequency interference, dispersion, fading and distortion. Figure 4 shows the transmission and reception of data using OFDM model. The stored HR data in the system is transmitted on the PLC model using OFDM technology. OFDM technique is applied in the following way: Inverse Fast Fourier Transform (IFFT) is implemented at the transmitter and Fast Fourier Transform (FFT) at the receiver so that the Inter-Symbol Interference (ISI) channel is modified into parallel ISI-free sub-channels with gains equal to the channel's frequency response values on the FFT grid. To eliminate Inter Block Interference (IBI) between successive IFFT processed blocks, Guard Interval (GI) of length not less than channel order is inserted in the entire transmitted block. In the receiver, GI is discarded in order to suppress IBI and converts the linear channel convolution into circular convolution (Zimmermann and Dostert, 2002; Wang et al., 2004). In OFDM transmission, the information symbols $s(n)$ are first converted into parallel blocks of length N as given in (2) and IFFT is performed on the blocks $F_N^H s(i)$;

$$s(i) = [s(iN), ..., s(iN + N - 1)]^T \quad (2)$$

The proposed framework of intelligent neural monitoring system

The system architecture includes three main subsystems, the devices for signals capturing, communication channels and intelligent software for system monitoring and interfacing. The procedures of the overall real time data monitoring system approach are: 1) Acquiring the electrical activity signals; 2) Processing of the biosignals; 3) Multiplexing the biosignals; 4) Transmitting the Multiplexed biosignals; 5) Reception of multiplexed biosignals; 6) De-Multiplexing the biosignals; 7) Displaying the biosignals separately; 8) Neural Interface and Analysis of signals; 9) Extraction of required features.

The electrical signal of human body (biosignals) will be first acquired and processed after removing the noise and the artifacts. Processing of the signals is achieved using

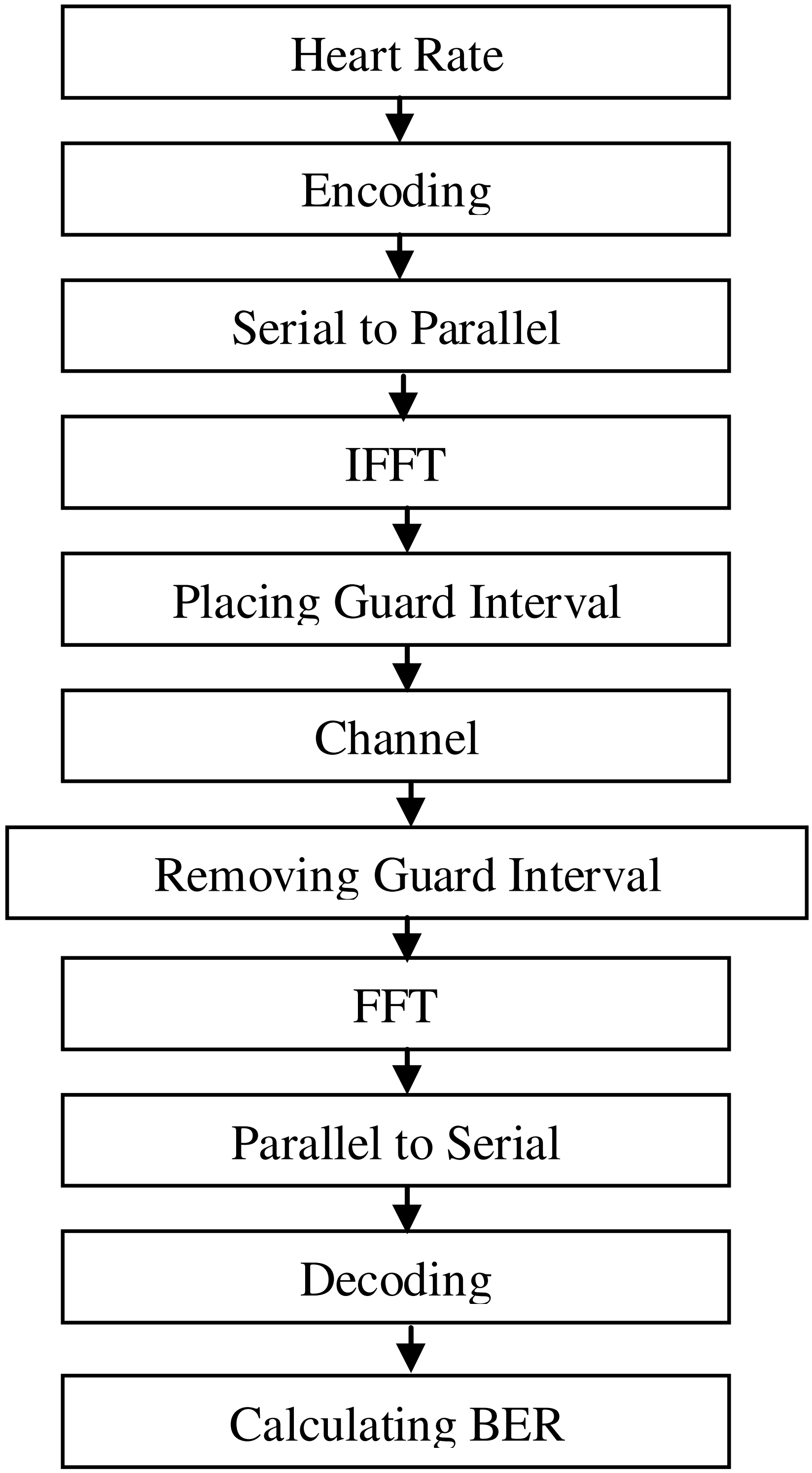

Figure 4. OFDM transmission and reception model.

Digital Signal Processor (DSP). The signals from the measuring and signal processing unit are converted from analog to digital converter. The analog to digital converter is used to convert the real continuous signal to discrete. These discrete signals will be then multiplexed together and transmitted as shown in Figure 5. In the receiver, signals will be de-multiplexed and separated. The DSP processor in the receiver side will process and convert

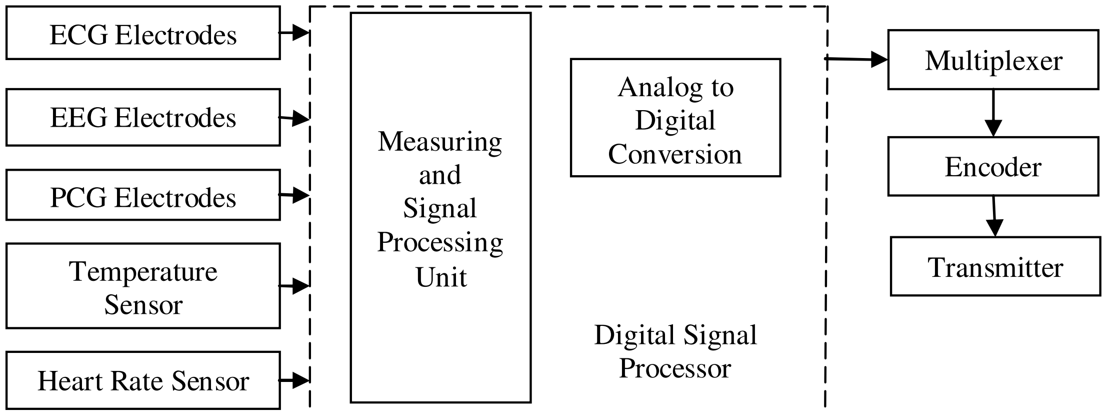

Figure 5. Block diagram for acquiring and transmission of biosignals.

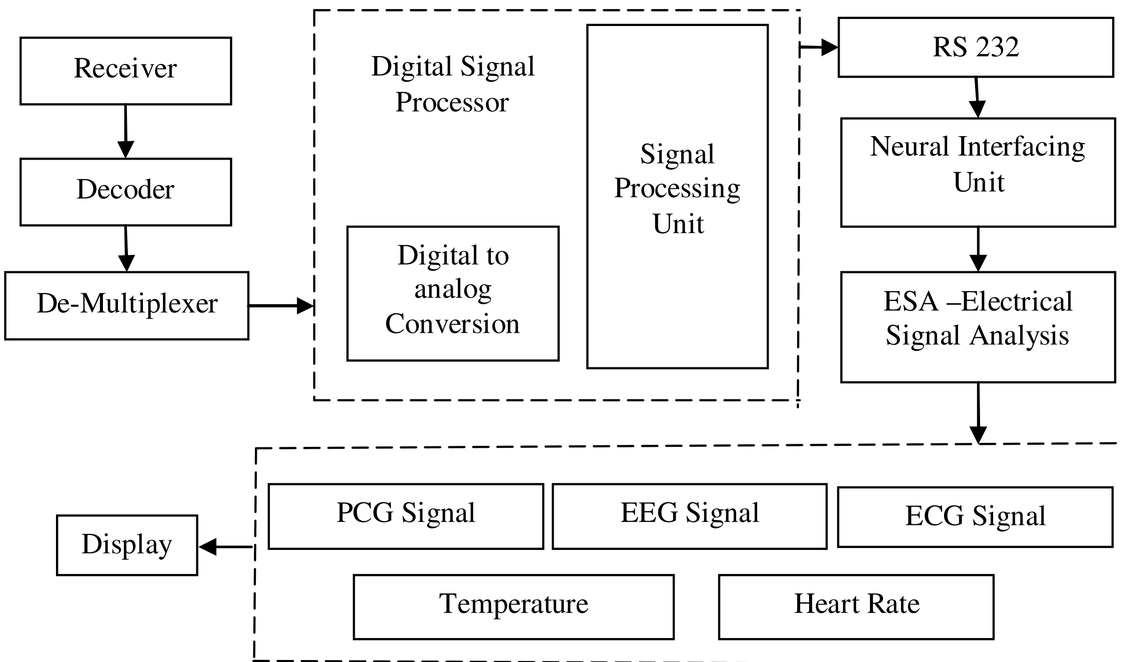

Figure 6. Block diagram for reception and analyzing of biosignals.

the discrete signal to continuous signal using Digital to Analog Convertor (DAC) as seen in Figure 6. These biosignals will be analyzed using the Neural Interface Unit and Electrical Signal Analysis block, after that, the required feature will be extracted. Two methods are utilized to transmit the signals; the first is by using wireless such as Radio Frequency (RF), specification for a suite of high level communication (zigbee) or GPS. The second method is PLC.

The block diagram of the overall INMS is shown in Figure 7. As seen from this figure, the electrical activity of the human body will be recorded in real time using the data acquisition module. The established data in the intelligent agent is stored in the patient database unit as well as transmitted through communication channel. The function of the neural interface unit is to compare the received data with the clinical database and for decision making.

The Intelligent agents have their origins in distributed artificial intelligence. Each agent is an independent methodology with reasoning capabilities working on a prescribed task. The intelligent agent implemented at a router should pose minimal computational overload. Here, the neural interfacing is used to get a faster classification for human body signals obtained by ECG, EEG etc. In neural network model, the node will consist

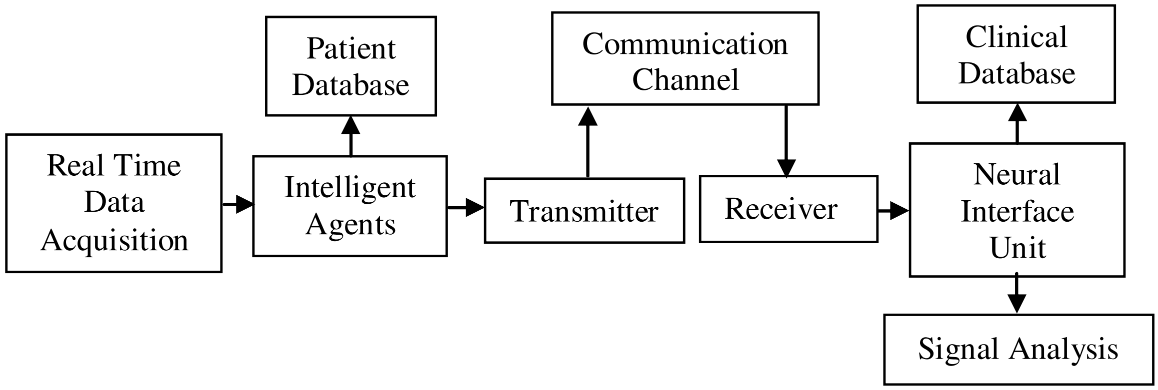

Figure 7. Overall block diagram of INMS.

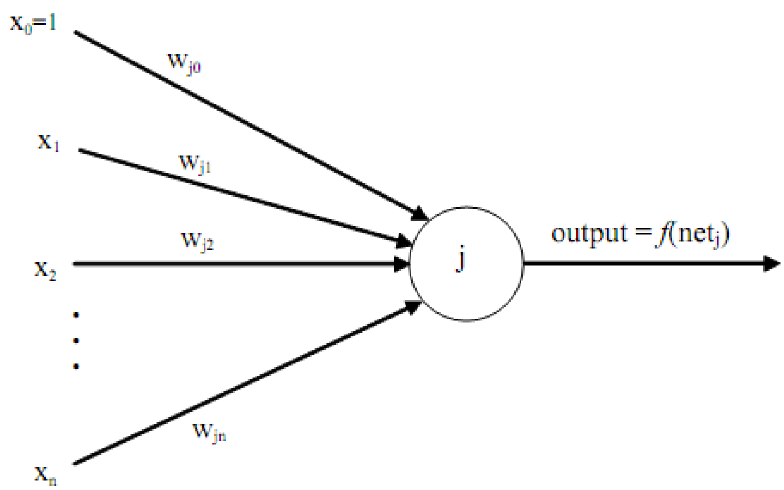

Figure 8. Neural network computation.

of inputs, weighted values and activation functions as shown in Figure 8. Each signal received from the input neurons is multiplied the corresponding connection strength, that is, weight. The Sums of weighted signals are passed through an activation function to the output neuron. Denoting the input signal by a vector $X(x_1, x_2, \ldots, x_n)$ and the corresponding weights to unit j by $W_j(w_{j1}, w_{j2}, \ldots w_{jn})$, the net input to the unit j is given by (Rezaul et al., 2006):

$$net_j = \sum_n W_{jn} X + W_{jo} = W_j X + b \qquad (3)$$

Where, $w_{jo} = b$ is a special weight called bias whose input signal is always +1.

The first pre-processing step is to collect training data sets (Electrical signal) recorded from human body. These data sets are used to train the network and obtaining the normalized values. In the majority of cases, detection of abnormal waves needs a preliminary feature extraction step, in which characteristics from the signal in time, frequency or time-frequency are extracted. The pattern recognition step involves the testing of intelligent systems dealing with the extracted and selected information in the previous step.

RESULTS AND DISCUSSION

A preliminary study of real time data transfer for the heart rate and temperature of human body was conducted using RF technology. Heart rate is measured by sentencing the pulse of the body. This pulse can be found at any point on the body where the pulse can be

Figure 9. Hardware for heart beat rate measuring.

Figure 10. Hardware for body temperature measuring.

found at any point on the body where the artery's pulsation is transmitted to the surface. Figure 9 shows the displaying value of the heart beat detected by sensor. Generally, the heat within the body is produced by the heart and circulatory system. Figure 10 shows the displaying temperature measured by temperature sensor. Different parts of the body have different temperatures. The commonly accepted average core body temperature (taken internally) is 37.0°C (98.6°F). The typical oral (under the tongue) measurement is 36.8±0.7°C (98.2±1.3°F).

The transmitter and receiver modules are shown in Figures 11 and 12 respectively. In the transmitter side, heart rate and temperature are measured and transmitted by means of RF technology. In the receiver, the RF signals are decoded and the heart rate and temperature are displayed. The measured values of the heart rate and temperature for certain time with regular time interval are illustrated in Table 3. As seen from this table, whenever there is a raise or fall in temperature, the heart rate also varies with temperature.

As for the PLC, a simulation study of data transmission has been carried out using Matlab program. The HR data measured by the prototype shown in Figure 9 is transmitted over PLC based on OFDM technique. This hardware was tested to assure the performance of sensor. To insure the high efficiency of the system, BER is applied to evaluate the performance of the OFDM. The results of this study are graphically shown in Figures 13, 14 and 15. These Figures show the BER Signal-to-Noise

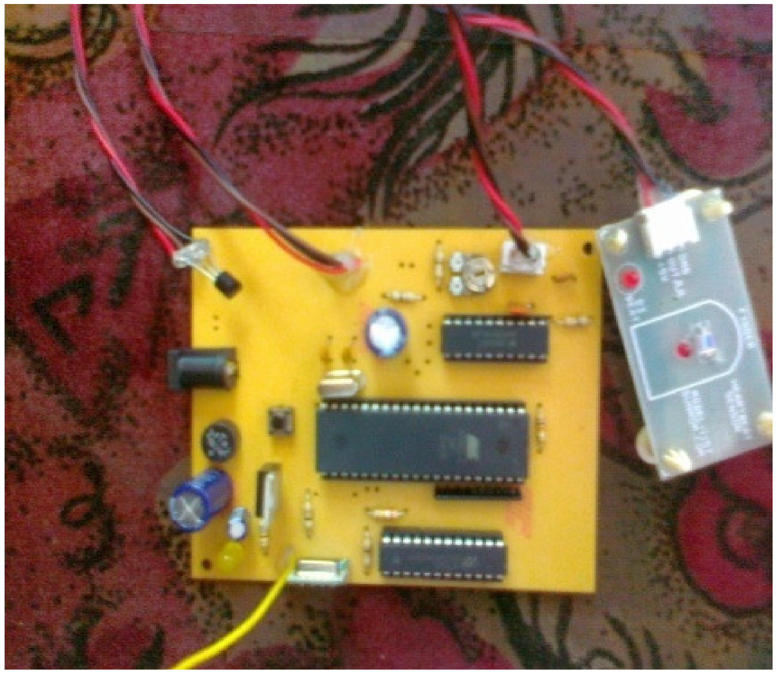

Figure 11. Transmitter module.

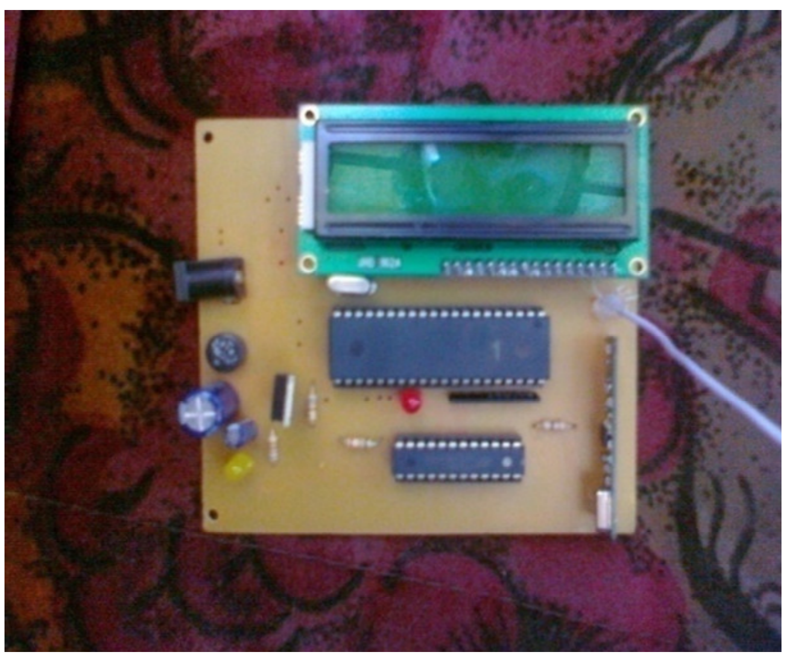

Figure 12. Receiver module.

Ratio (SNR) for different IFFT. In the simulation, the size with guard time was changed in the range of 20, 32, and 48 as seen in Figures 13, 14 and 15 respectively. From these figures, it is seen that as the IFFT size is increased the BER is decreased. When guard time is more than 25 percentage of IFFT size, the BER is reduced.

A certain analysis on the ECG signals such as FFT, Continuous Wavelet Transform (CWT), Histogram equalization and Power Spectral Density (PSD) were carried out and the corresponding output waveforms are

Table 3: Measured values of the heart rate and temperature

Time	Temperature	Beats/ Minute
10:00	33	60
10:05	33	61
10:10	34	66
10:15	34	68
10:20	35	72
10:25	33	61
10:30	35	73
10:35	36	82
10:40	36	81
10:45	35	76
10:50	35	74
10:55	34	68
11:00	35	75

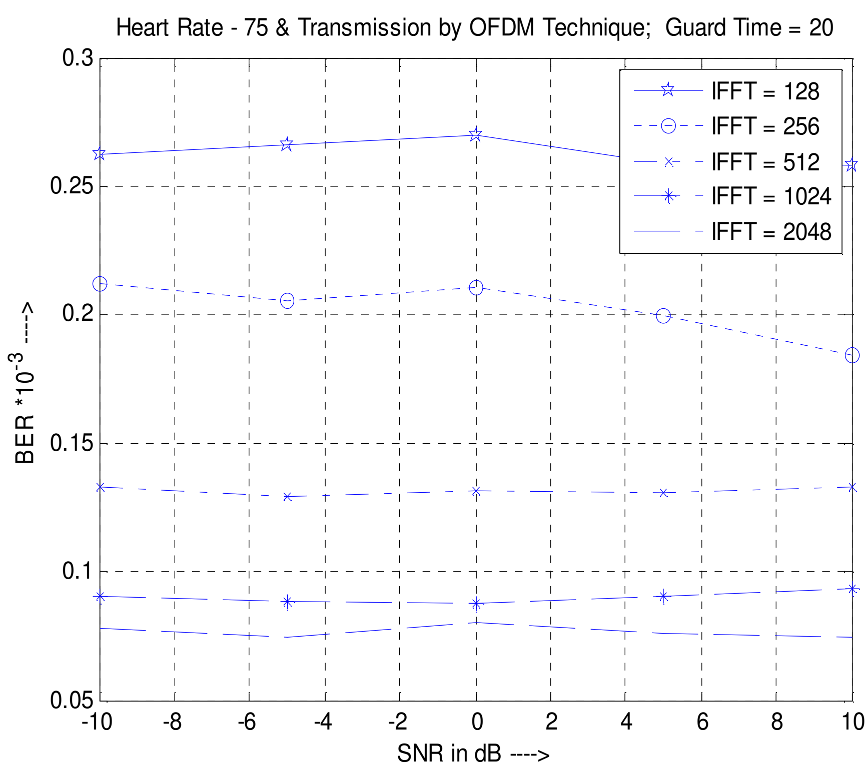

Figure 13. BER SNR (guard time = 20).

demonstrated in Figures 16 to 20. The continuous ECG signals are depicted in Figure 16. FFT is an efficient algorithm to compute the discrete Fourier transform (Robert, 2004). It can be used for non-stationary signals, where spectral components exist in the interested signals. As seen from Figure 17, when FFT is applied to the simulated ECG signal the output is scattered and no details can be inferred from that since it decomposes the signal into its frequency component and amplitude. Histogram equalization is a method in image processing of contrast adjustment using the image's histogram (Robert, 2004). When histogram equalization is performed for the ECG signal a peak appears in the range from 4 to 7 as shown in Figure 18.

CWT is used to divide a continuous-time function into wavelets. Unlike Fourier transform, the continuous

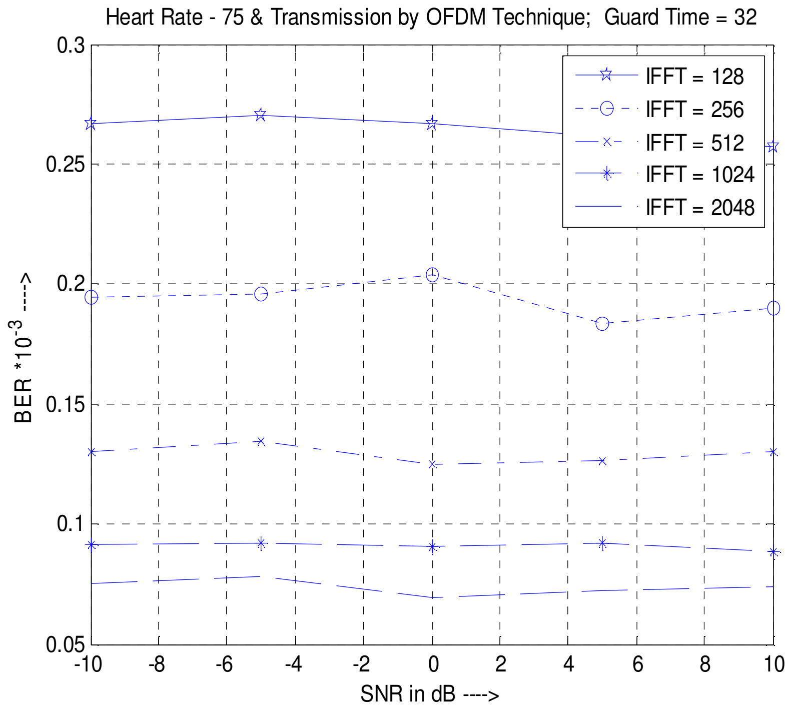

Figure 14. BER SNR (guard time = 32).

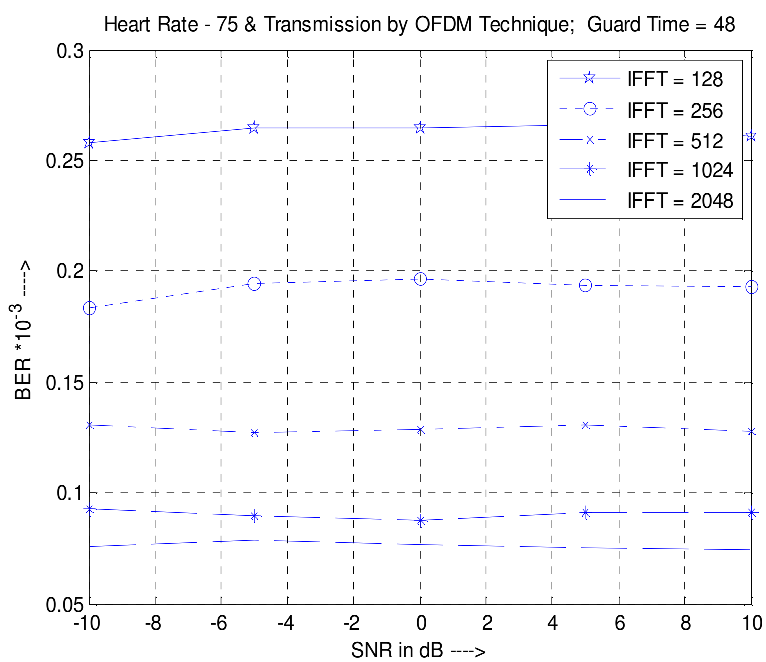

Figure 15. BER SNR (guard time = 48).

wavelet transform possesses the ability to construct a time-frequency representation of a signal that offers very good time and frequency localization (Sabarimalai and Dandapat, 2007). When ECG signal is subjected to CWT few peak in the range of 150 to 300 in the sampled region as seen in Figure 19. PSD is a positive real function of a

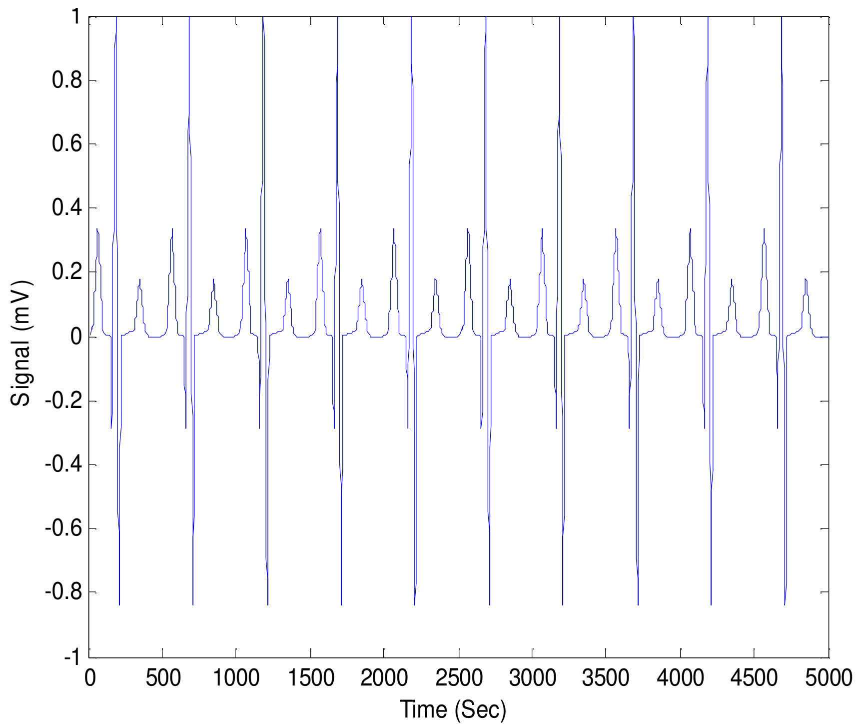

Figure 16. Continuous ECG waveform.

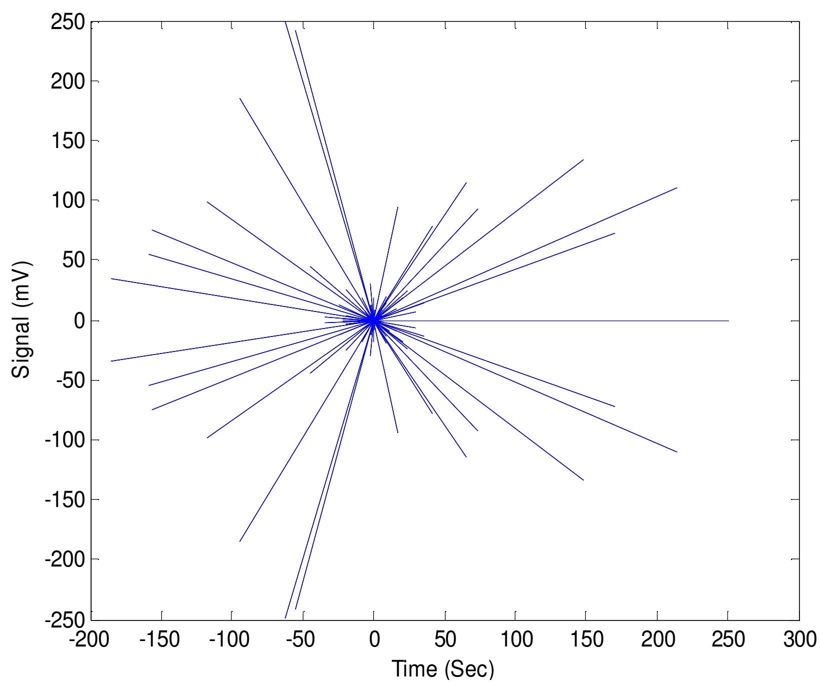

Figure 17. Output after applying FFT.

frequency variable associated with deterministic function of time, which has dimensions of power per Hz, or energy per Hz. Intuitively, the spectral density captures the frequency content of a stochastic process and helps identify periodicities (Patel et al., 2011). PSD is estimated using periodogram method. Figure 20 shows

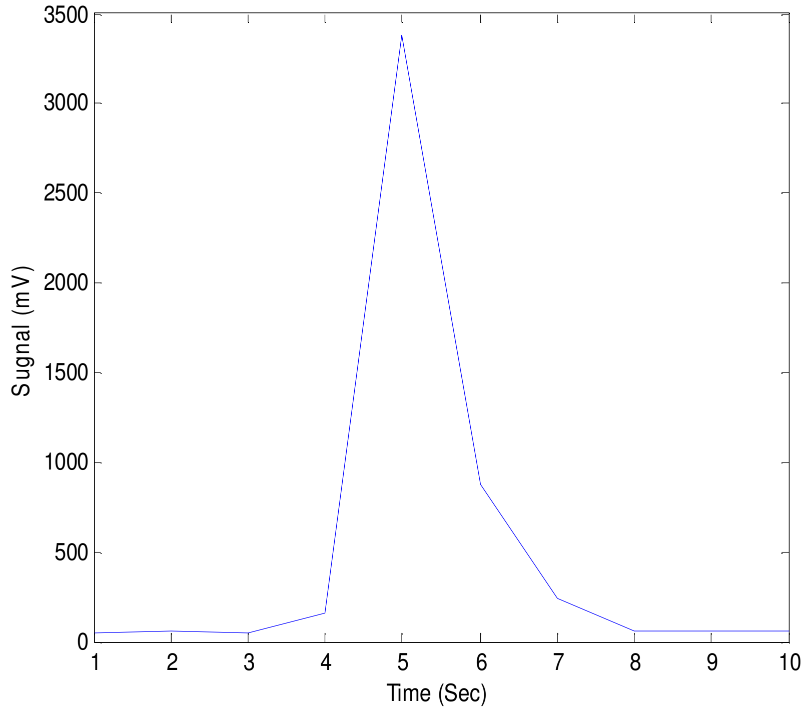

Figure 18. Output after applying Histogram.

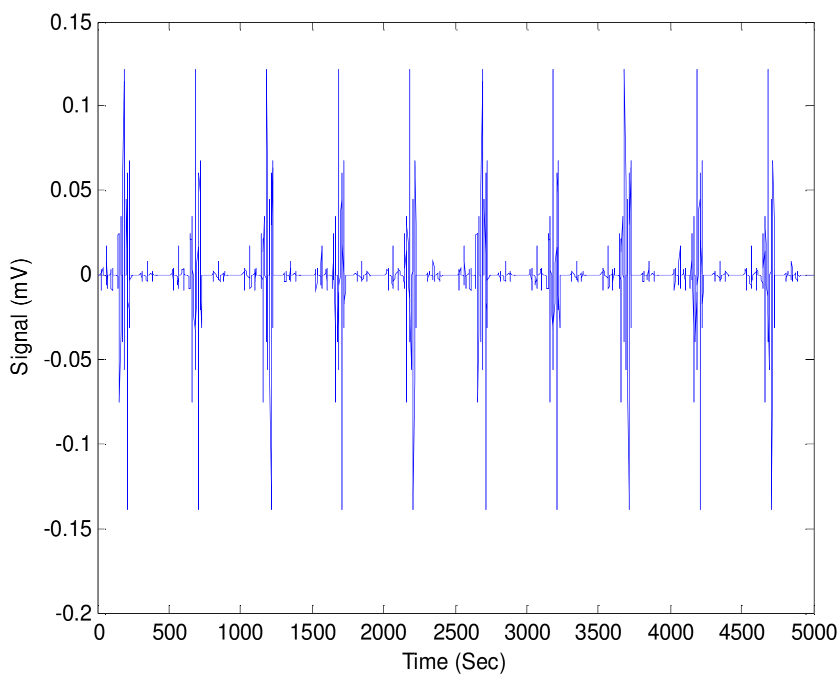

Figure 19. Output after applying CWT.

the output after applying PSD on the ECG signal. It is used to check whether the person is in aware and exhaustion states.

CONCLUSION

This paper presents a review on the techniques used for

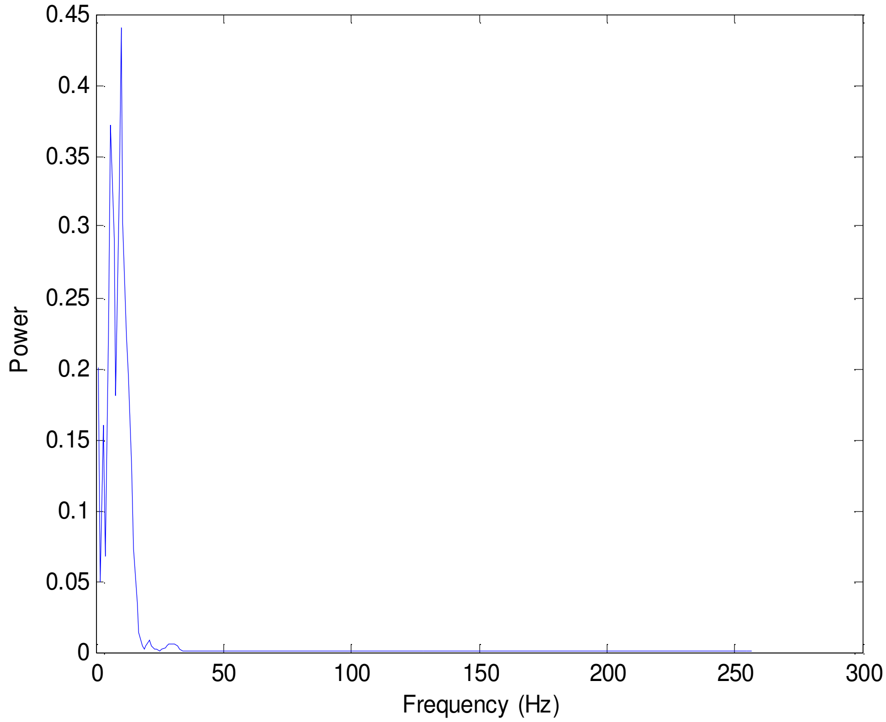

Figure 20. Applying PSD for the simulated ECG waveform.

medical data monitoring systems. A prototype of measuring system with wireless medical data transfer based on RF is tested. A developed simulation scheme was implemented using Matlab program for PLC as a channel to transmit the HR using OFDM technique. The simulation results on the signals of human body detected by ECG were analyzed using different method. In addition, a framework of INMS based on PLC was discussed for feature works on this project. It is noted that the noise is the most crucial factor degrading high-speed data transmission over PL networks. However, PLC has the advantage of being an independent communications network where existing cable infrastructure can be used for dual purposes. The availability of PLC technologies is increasing rapidly and provides huge opportunities for home monitoring applications in particular for outpatients and patients suffering from chronic diseases.

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