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ECG Wavelet Compression for Transmission over IoT Networks

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Abstract: - Public healthcare has been become appeared an increasing attention given the exponential growth human population and medical costs. Electrocardiogram (ECG) has an important role in the diagnosis of heart disease. Therefore, care for children, youths and the elderly along with a wide diversity of patients can be applied. This can be achieved through the internet of things. The Compression of digital Electrocardiogram (ECG) signals is desirable for three reasons. These reasons are economic use of storage space for databases, reduction of the data for transmission on the Internet of Things (IoT), and decrease power consumption in transmitting data from the battery 24 hours. This paper deals with the discrete wavelet-based compression method. The software results are obtained by using the MATLAB program. The improvement in the bit error rate (BER) from the original signal to the reconstructed one is about 0.4%. The achieved average compression ratio (CR) is about 12.832%. The achieved percent root mean square difference (PRD) in the mean is about 0.2987 %. The achieved signal-to-noise ratio (SNR) is about 32.2486 dB. The hardware implementation of a compressed ECG signal is performed by using the internet of things (IoT) system. This IoT system is based on the SD card sensor and interfaced with the ESP8266 Wireless Module that is connected to Cloud through the MQTT server. The power consumption of the design reduces about 13.21% from battery energy. This is achieved through hardware implementation. The ECG signals can be obtained without loss of signal shape. The best results are obtained with the Sym20 filter.

Keywords: - Internet of things, Electrocardiograph, discrete Wavelet transform, Signal to Noise ratio, Percent Root Difference, Compression Ratio.

I. Introduction:-

Electrocardiogram ECG is a graphical illustration of electrical impulses that are produced from cardiac muscles due to its ionic activity. ECG has a critical role in the diagnosis of heart diseases where every arrhythmia in ECG signals refers to heart disease [1]. Normally one signal differs from other signals while sometimes one disease has different signals from the patient's ECG signals. The useful bandwidth of an ECG signal can range from 0.5-100 Hz [2], sometimes reaching up to 1 kHz. The ECG recordings are sampled at 360 Hz and the resolution of each sample is 11 bits/sample [3].

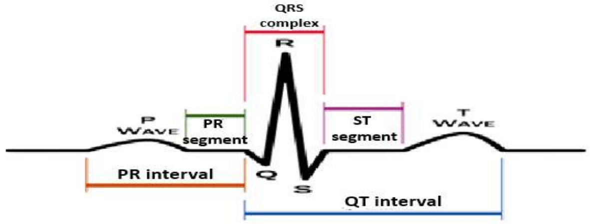

Fig.1 The ECG signal

Figure 1 shows an example of a normal ECG trace, which consists of a P wave, a QRS complex, and a T wave. The P wave is the electrical signature of the current that causes atrial contraction. The QRS complex corresponds to the current that causes contraction of the left and right ventricles. The T wave represents the period of time when the ventricles repolarize. Most of the ECG signals energy is concentrated in the QRS complex. However, there are diagnostically important changes in the low amplitude PQ and ST intervals, the P and T waves [4].

ECG signals recorded from patients are used for monitoring and diagnostic purposes. ECG signal can be stored as digital data for use in further processing for Telemedicine applications. A huge amount of data is a big issue for storage or transmission. Therefore, the ECG signal compressed to reduce the memory space in ECG databases. This reduces the transmission period of real-time ECG signals over cloud networks for the internet of things.

By 2022, unprecedented growth in the Internet of Things (IoT) technologies will make it possible to talk approximately 50 billion connected devices through the internet [5]. The Internet of Things (IoT) represents a set of interconnected smart objects and people at any time and any place. This is performed by using any network and any services. IoT has a strong effect on healthcare. It is a platform extends from sensors, local processors, wireless transmitters, and central communications stations [6].

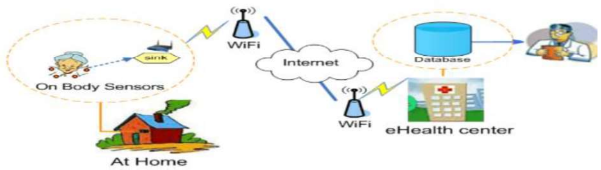

Fig. 2 IOT healthcare

Figure 2 shows the trend for IoT healthcare devices. It incorporates wide sectors that involve many individuals. The main feature of the IoT healthcare platform is the communication between a wearable sensor and a central system [7]. In this way, doctors could easily assess patients. In terms of health conditions, it includes early diagnostics, emergency, and chronic diseases.

IoT-based solution has been enabled from a wide range of technologies. Advanced electronic solutions have represented an effect on the fast growth of IoT solutions. Main technologies to enhance IoT-based healthcare services such as Ultra-Low Power, Big Data, and Communication Networks.

IoT-based healthcare services have challenges that arise from the sensors and communication networks as energy consumption and cost. Therefore, ECG signal compress is reducing the time of period for ECG signal by using wavelet transform. A wavelet transform is simply a small wave that has energy concentrated in time. This gives a tool for the analysis of transient, non-stationary, or time-varying signals. The wavelet transform has evolved as a powerful mathematical tool in the field of data compression. Wavelet transforms are broadly divided into three classes: continuous, discrete, and multiresolution-based. In the framework of ECG signals, Analyses of discrete wavelet transform (DWT) signals in both time and frequency domains. Are suitable for the analysis of time-varying non-stationary signals such as ECG signals [8].

For a one-dimensional ECG signal, each convolution-based 1D-DWT can be realized using a pair of filters. In the decomposition stage, the original signal x of length L is passed through a low pass filter (LPF) and a high pass filter (HPF). Then, the two filtered are down-sampled by two to obtain two sub-bands LPF and HPF, respectively. In the reconstruction phase, LPF and HPF are up-sampled by two and passed through another set of filters. These filters are called the synthesis (reconstruction) filter pair [l, h], to reconstruct the signal. In this paper, the discrete wavelet transform will be used to compress ECG signals for transmission over the internet of things. This reduces the power consumption from the battery. The amount of data is reduced without losing information with high quality. The present paper is organized into five sections. The introduction is presented in Section 1, while Section 2 is dedicated to the literature review. The ECG compression using DWT is discussed in Section 3, whereas (the hardware and software) experimental results and discussion are presented in Section 4. Finally, the paper is concluded in Section 5.

II. Literature review

Many researchers have worked on compression of ECG signals. They have applied different types of wavelet transforms. They have been many efforts also in the field of IoT based remote patient monitoring systems. Most of the researchers have used Matlab software for ECG compression. Some researchers are done such as:

H.Khorrami and others [9] have compressed ECG signals using DWT and CWT. Mean square error (training) of 0.0349 and Mean square error (testing) of 0.0438 was achieved when evaluated using Matlab software. DWT-MLP and CWT-MLP achieved 0.0056 and 0.1048 respectively. As for A.Dallali and M. Samet [10] have extracted ECG signals using Daubechies discrete wavelet transform of decomposition level 3. The accuracy achieved 99.99 % when evaluated using Matlab software. However, S. M. Jadhav, S. L. Nalbalwar, and A. A. Ghatol [11] have extracted ECG signals using discrete wavelet transform. Specificity, Sensitivity, and Accuracy achieved 93.1%, 93.75%, and 86.67% respectively. However, Z. Zidelmal and J. Merckle [12] have extracted ECG signals using db4 Discrete Wavelet Transform, Data normalization, R peak detection- wavelet coefficient, Q, S peak- simple peak detection method. Average accuracy with no rejection and Minimal classification cost achieved 97.2% and 98.8% respectively. Features from Prof A.Muthuchudar and S. S. Baboo [13] were extracted QRS amplitude, P wave, T wave, PR interval, and ST interval by using discrete wavelet transform. A Low pass linear phase filter is used for noise removal. A median filter is used for baseline correction. An average accuracy of 96% achieved when evaluated using MATLAB software. X. Tang and L. Shu [14] have extracted ECG signals Baseline wanders removal and denoised. The ECG signal is passed through a low pass filter (LPF) and a high pass filter (HPF) by using DWT, reduction rough sets. Compress ECG signals are calculated by the Matlab software database. Accuracy achieved 91.7 %respectively. Therefore, Anand Kumar Patwari and others [15] are used dB and sym discrete wavelet transform for decomposition level 3 like A.Dallali and others. There have found that the compression ratio is increasing with the increment in the order of the wavelet. They are achieved that the difference between two PRD values is less than 0.1 or 10% for all the wavelets as desired. But this research shows the effect of the Internet of Things with health care Darshan, K. R., and K. R. Anandakumar [16] have enhanced the quality and efficiency of Health care and to respond to widespread public health emergencies through the acquisition, management, and use of information in health using IoT. So Sapna and Amit Agarwal [17] concentrated on the roles and features of IoT in healthcare. I also discussed the technologies that make this IOT possible in healthcare. This is proposed by how cloud used to follow healthcare anywhere. Hence, Michael Hempel and others [18] focused on analyzing the effects of truncation strategies employed in wavelet-based compressors on the reconstruction error of the signal. Xiaoyan Xiang and Jianyi Meng [19] have presented an electrocardiogram (ECG) compression processor for wireless sensors. The proposed processor only takes with a low power consumption of 92nW. Compression ratio of 2.71 for lossless, 14.9 for lossy compression ratio and low PRD of 0.39% achieved when evaluated using MATLAB software. Those Ram K. Kanhe and others [20] have derived a low pass filter from compression using DWT is carried out. CR, PRD, and CCC achieved when evaluated using Matlab software. They are achieved that the quality of the reconstructed signals is excellent with minimum loss of the diagnostically important features. Zhaoyang Wang and others [21] have effectively removed high-frequency noise while retaining and enhancing weak features. Their used with db4 and sym4 wavelets and compared them. They are achieved to improve the signal to noise ratio and reduce the mean square error.

This paper introduces two contributions. The first contribution presents a discrete wavelet transform to compress ECG signals for transmission over the internet of things. The amount of data sent is reduced without affecting the signal quality. The signal quality was checked after compression through the BER, CR, PRD, and SNR when evaluated by using the Matlab software. The second contribution shows the ratio of energy consumption from the battery. There are different types of Wavelet filters with different scales and frequencies. As the scale of the wavelet filters increases, the frequency of the output signal decreases with low power consumption of the battery. This work was hardware implemented by using one node MCU, Message Queuing Telemetry Transport (MQTT) server, current sensor, and battery.

III. ECG Signal Compression Using Discrete Wavelet Transform

A. Discrete wavelet transform (DWT)

Discrete wavelets are over formed from a mother wavelet, but with scale and shift in separate phases. The wavelet transform is simply a small wave that has energy concentrated in time. In the framework of non-stationary signals, wavelet transform analyses signals in both time and frequency domains, and therefore it is suitable for the analysis of time-varying signals such as ECG [22, 23].

This shows that the wavelets an ideal tool for analyzing signals with sharp changes or discontinuities while their compactly supported nature enables temporal localization of signals features. There are several time-frequency methods available for the decomposition of the high-resolution signals. This effect is obtained by scaling (contractions and dilations) as well as shifting the basis wavelet. DWT of ECG signal f (t) as [22]:

$$f(t) = \sum_{j=1}^{l} \sum_{k=-\infty}^{\infty} d(j,k).\varphi(2^{-j}t-k) + \sum_{-\infty}^{\infty} a(l,k).\emptyset(2^{-l}t-k) \quad (1)$$

Where $\theta(t)$ the scaling is function, $\varphi(t)$ is the mother wavelet, $d(j,k)$ is the detail coefficient at scale j and $a(l,k)$ is the approximation coefficient at scale. The expression for element coefficients and approximation are given underneath

$$d(j,k) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{\infty} f(t).\varphi(2^{-j}t-k)dt \quad (2)$$

$$a(j,k) = \frac{1}{\sqrt{2^l}} \int_{-\infty}^{\infty} f(t).\emptyset(2^{-l}t-k)dt \quad (3)$$

For a one-dimensional ECG signal, each convolution-based 1D-DWT can be realized using a pair of filters. In the decomposition stage, the original signal x of length L is passed through a low pass filter (LPF) and a high pass filter (HPF). Each step of retransforming the low-pass output is called dilation and the maximum of dilations can be performed will result in a single low-pass value and a single high-pass value. The procedures of the wavelet decomposition of the ECG signal as shown in Figure 3.

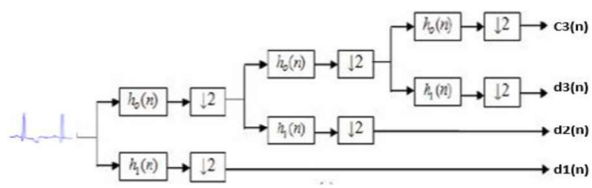

Fig.3 decomposition of level3 forward DWT

As shown in figure 3 that each stage of this scheme consists of two digital filters and two down samplers by 2. The ECG signal is separated into two types of filters through wavelets. The first filter $h_1(n)$ is the discrete wavelet high-pass filter and the second $h_0(n)$ is its mirror version low-pass filter. The down-sampled outputs of first high-pass and low-pass filters provide the detail and the approximation respectively. The first approximation A1 is decomposed and this process is continued. The impulse responses $h_0(n)$ (low-pass filter) are derived from the scaling function and the mother wavelet. This presents a new interpretation of the wavelet decomposition where splitting the ECG signal into frequency bands.

The process of decomposing the signal x can be reversed, respectively. It is given the approximation and detail information. It is possible to reconstruct x with the use of up sampling as shown in figure 2.

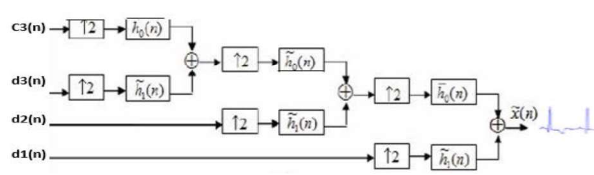

Fig.4 inverse DWT

As shown in figure 4, this process can be shown as up sampling (by a factor of 2) followed by filtering the resulting signals and adding the result of the filters. The impulse responses $h_0(n)$ and $h_1(n)$ will be derived from $h_0(n)$ and $h_1(n)$.

The concept of being able to decompose a signal and then perfectly reconstruct the signal again is important. In order to make use of this tool, it is necessary to analyze ECG signals the wavelet coefficients to identify characteristics of the signal that were not apparent from the original time-domain signal.

B. Test steps

For ECG compression, the four most common steps are used. There are to obtain Database, DWT decomposition, thresholding, and Entropy encoding. The block diagram for the proposed method shown in Figure 5. Here, the compression methodology illustrated in the following four steps.

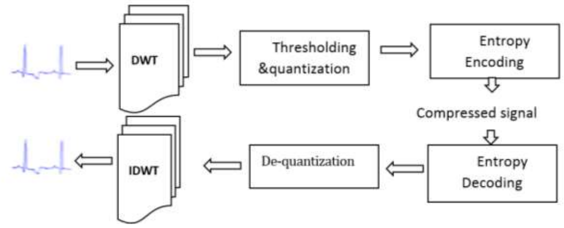

Fig.5 Block diagram for proposed method

Step 1. Database

The first step in ECG signal processing is to obtain it from the Matlab program database, available online [3]. Different ECG signal records are used for experiments. An algorithm is tested from each record 100.dat, 106.dat, and 117.dat. The database is sampled at 360Hz and the resolution of each sample is 11 bits/sample over a 10mV range which taken the 1 minute ECG signal. To obtained wavelet analysis by using the Matlab program. As shown in Figure 6, the ECG signal is decomposed using sym 20 wavelet filters for 117 records.

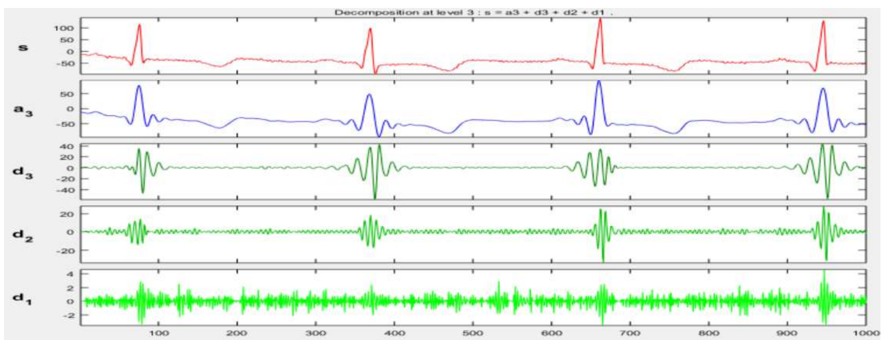

Fig.6 ECG signals decomposition using sym20 Wavelet for 117.data

As shown in figure 3, there are decomposition results of precipitation by the "sym20" mother wavelet under level 3. The decomposition level contains three detailed sub-signals and one of approximate sub-signal.

Step 2. Decomposition

In this step, the mother wavelet is chosen, Then DWT decomposition is performed on the ECG signal. Several various criteria will be used for selecting the best wavelet filter. Such as, the wavelet filter must minimize the reconstructed error contrast, maximize signal to noise ratio (SNR) and minimize The Percent Root Mean Square distortion (PRD). In general, the mother wavelet filters are selected based on the power conservation properties in the approximation part of the wavelet coefficients. After that, the level of decomposition for DWT is selected which depends on the type of signal being analyzed. Here, the different wavelets are used as the wavelet filters. The levels of decomposition is applied to the ECG signals various.

Step 3. Thresholding

After computing the wavelet transform of the ECG signal, thresholding is applied to the wavelet coefficients of each level from 1to N. Many of the wavelet coefficients are zero or approximate to zero. By applying thresholding (level or global), the coefficient below the level is zero, which leads to a many consecutive zero's which can be stored in much less space and transmission speed is high. Besides, in the case of Global thresholding, the threshold value is set manually. This value is chosen from the wavelet coefficient (0….x_{max}j) where x_{max}j is the maximum coefficient in the decomposition.

Step 4. Encoding

In this step, signal compression is achieved by efficiently encoding the truncated the small valued coefficients. The resulting signal data contains the same redundant data which a waste of space. In this paper, run-length encoding is applied to the redundant data to avoid the redundancy problem without any loss of signal data. Run-length coding is considered as a simple form of data compression. In it, runs of data are stored as a single data value and count, rather than as the original run [24]. Then for web communication, the compressed data are transmitted between the server and client. Finally, an inverse discrete wavelet transform is performed at the end to check the ECG signal.

C. Simulation Results

In this part, a wavelet filter methodology has been used for ECG signal compression. Haar, Debauches, symlet, bior, demy, and Coiflet wavelet are considered as different types of wavelet filters for signal decomposition. The performance of the wavelet filters in the field of ECG signal compression can be evaluated by matching the reconstructed signal to the original signal. For this, the following parameters are considered as [25]:

- Compression ratio (CR):

$$CR = \frac{\textit{Bit rate of the original signal}}{\textit{Bit rate of the compressed signal}} \quad (4)$$

- Signal to Noise Ratio (SNR):

$$SNR = 20 * \log_{10} \frac{\sum {x_0}^2(n)}{\sum[x_o(n)-x_r(n)]^2} \quad (5)$$

- Percent Root Mean Square Difference value (PRD):

$$PRD = \sqrt{\left[\frac{\sum_{n=1}^{N}[x_o(n)-x_r(n)]^2}{\sum_{n=1}^{N}[x_0^2(n)]}\right]} *100 \quad (6)$$

Where $x_o(n)$ and $x_r(n)$ are the original and reconstructed signals of length N, respectively. The PRD indicates reconstruction fidelity by pointwise comparison with the original data. Another definition of error measure called PRD (mean) is the same as PRD (value) but it subtracts the average value of the signal is given by:

$$PRD = \sqrt{\left[\frac{\sum_{n=1}^{N}[x_o(n)-x_r(n)]^2}{\sum_{n=1}^{N}[x_o(n)-\text{mean}(x)]^2}\right]} *100 \quad (7)$$

Mean(x) is the average value of the signal.

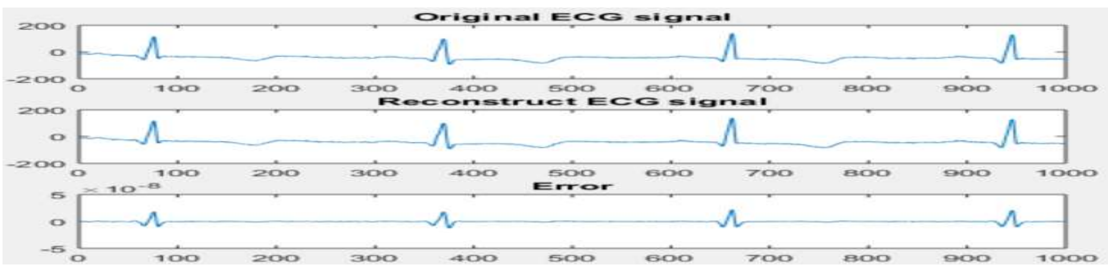

Fig.7 Reconstruct of ECG signal and error ratio using sym20 Wavelet for 117.data

Figure (7) gives the results of the original signal, the reconstructed signal, and the error signal. The error signal is from the original signal (record 117). 1000 samples from the ECG signal are compressed and reconstructed by the decomposition of level 3 with the symlet 2o filter. The error ratio is obtained to reconstruct the ECG signal from the original one with 0.4%.

The results of the CR, SNR, and PRD (mean and value) for three various types of the ECG signals are shown in the following figures.

- For ECG signal 100.dat (male) record

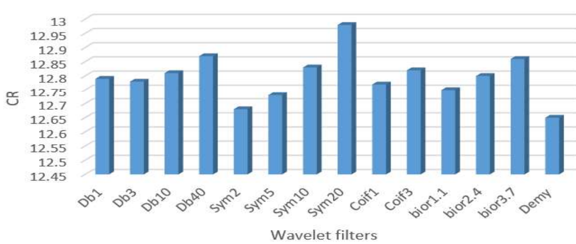

Fig 8. Plot of CR with various wavelet filters

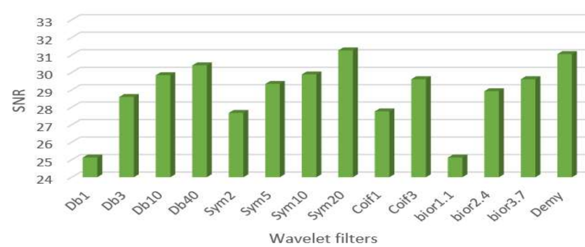

Fig 9. Plot of Signal to Noise ratio various Wavelet filters.

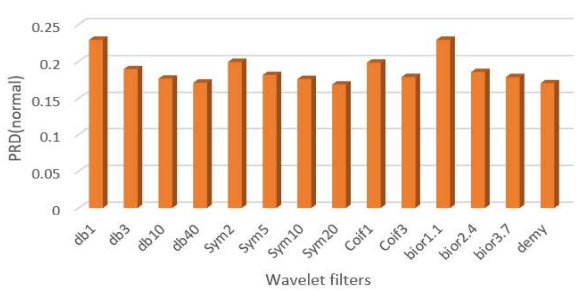

Fig 10. Plot of PRD with various wavelet filters

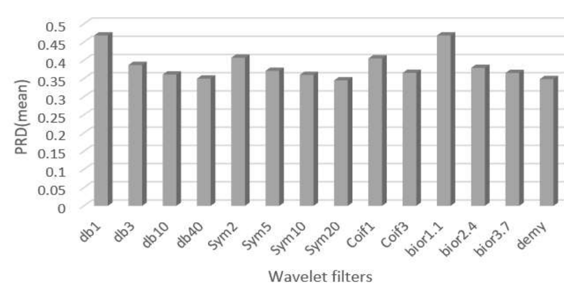

Fig 11. Plot of PRD (Mean) with various wavelet filters

- For ECG signal 106.dat (female) record

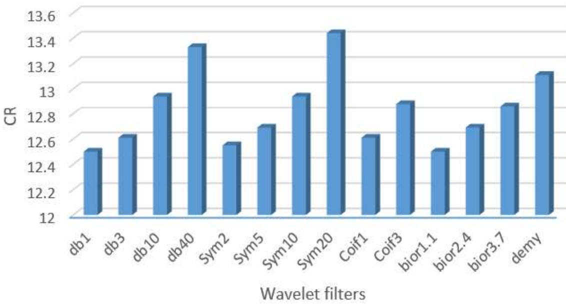

Fig 12. Plot of CR with various wavelet filters

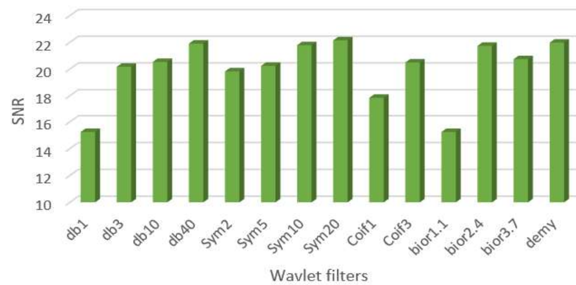

Fig 13. Plot of Signal to Noise ratio various Wavelet filters.

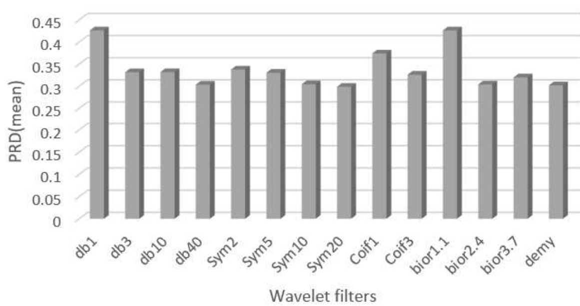

Fig 14. Plot of PRD with various wavelet filters.

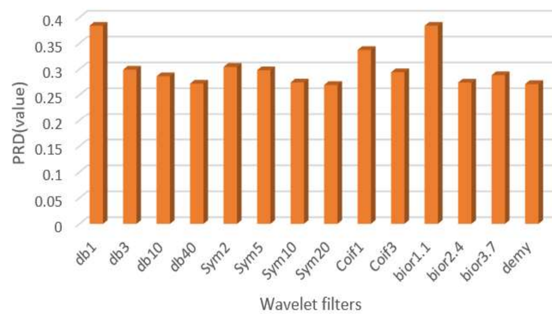

Fig 15. Plot of PRD (Mean) with various wavelet filters.

- For ECG signal 117.dat (male) record

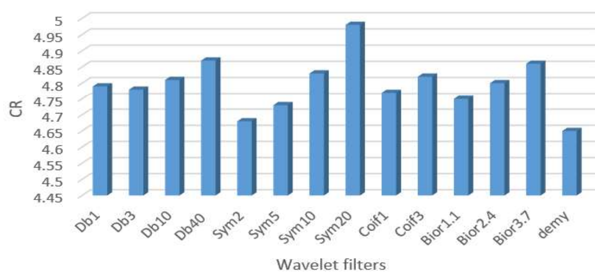

Fig 16. Plot of CR with various wavelet filters.

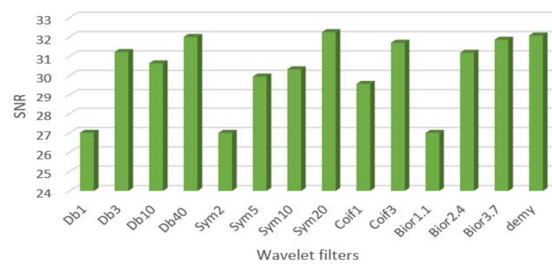

Fig 17. Plot of Signal to Noise ratio Wavelet filters.

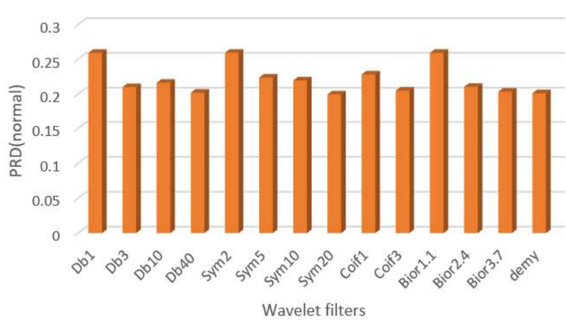

Fig 18. Plot of PRD with various wavelet filters.

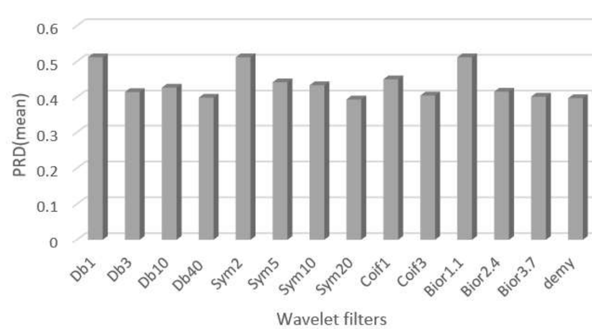

Fig 19. Plot of PRD (Mean) with various wavelet filters

Figures (8-19) give the results of the maximum CR, SNR, minimum PRD (normal), and PRD (mean) values that are obtained from the sym20 wavelet filter. Sym 20 is the best type of wavelet filters. An increase in the order scale of each type of the wavelet filter achieves the best results as shown in the previous figures.

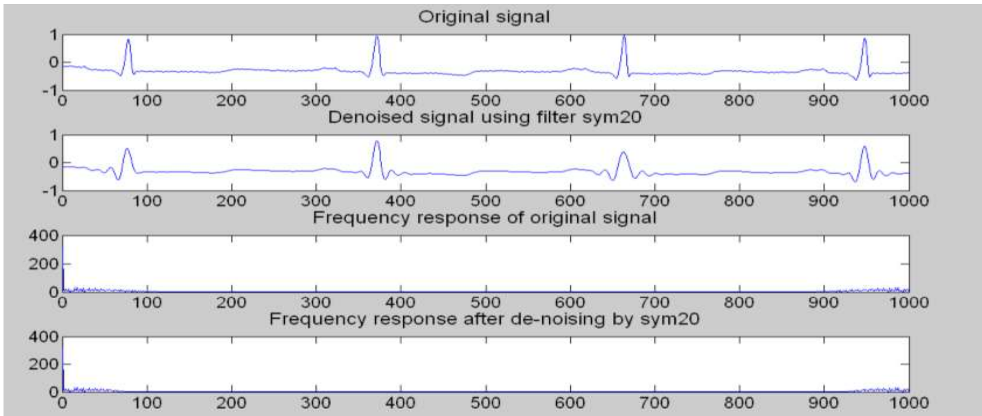

Fig.20 Original Signal, Denoised Signal Using Sym20, Frequency Response of Original Signal and Frequency Response after Denoising by Sym20.

As shown in figure 20, the frequency response of the original signal is the same as frequency Response after Denoising by Sym20 that indicate sym 20 has become the best type in the ECG signal filter.

IV. Design implementation test

A. Hardware model

The design proposed in the previous part (III), in IoT based ECG monitoring framework, is actualized utilizing the propelled procedures of portable monitoring. Insights about the monitoring node, the main function is collecting ECG data and that sending this information anywhere by the MQTT server. As portrayed in Figure (21), the ECG monitoring node in our framework, for the most part, incorporates: 1) SD card, 2) MCU ESP V32, 3) current sensor, 4) Arduino Uno, 5) Power module and 6) Main Procedures of Data Transmission through the IoT cloud.

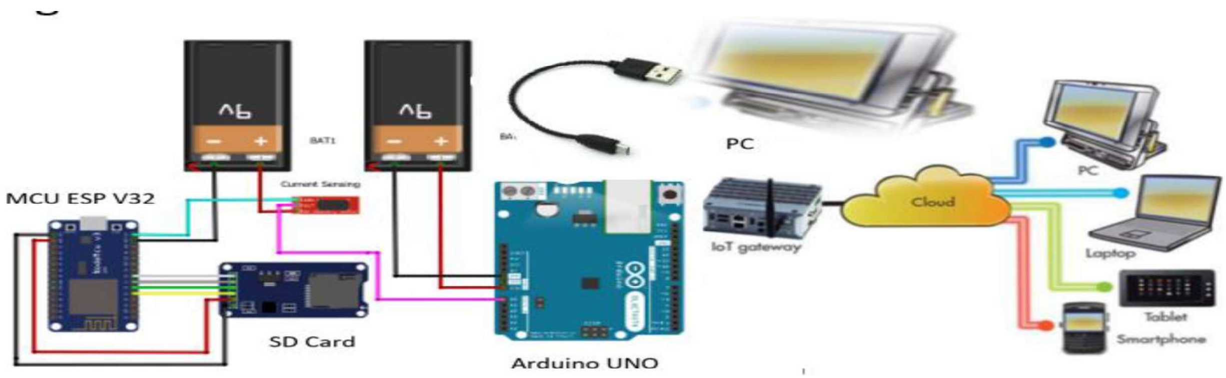

Fig.21 schematic diagram of the proposed smart healthcare system design in fritzing.

1) SD card :

The micro- SD Card Module is a simple solution for transferring and saving ECG signal records to and from a standard SD card. The pinout is directly compatible with Arduino, but can also be used with other microcontrollers. It allows you to add mass storage and signal logging to this work.

2) MCU ESP V32:

Node MCU is an open-source tool and development kit that supports us to prototype our IoT product. Node MCU is an ESP8266 Wi-Fi at 3.3V logic and microcontroller at 80MHz. It is widely used in IoT implementation. We can program the microcontroller using the Arduino IDE software for an easy to run the Internet of Things. The features are open-source, programmable, low cost, interactive, simple and Wi-Fi supported. Node MCU also likes Arduino hardware IO that can dramatically reduce the redundant work for configuring and manipulating hardware code like Arduino.

3) Current sensor:

The ACS712 Current Sensor is a cool little device for making current measurements. Better, it is easy to use with an Arduino, to show Change in current depending on wavelet selection.

4) Arduino Uno :

The Arduino Uno is an open-source microcontroller board based on developed by low-level language. The board is Use this medium to display the results of power on the plx.xls. Theirs consumed by ESP8266 in sending data in various types of wavelets and the ability to know the energy consumed.

5) Power module:

The power module gives a solid vitality power supply to each module in the ECG monitoring node. Two methods of intensity supply are accommodated as the USB and the lithium battery due to their long lifetime and high compactness.

6) Main Procedures of Data Transmission through the IoT cloud:

With the help of the IoT cloud, the ECG signal can be easily obtained for any patient from anywhere through the MQTT server. Regardless of the patient himself or herself, any doctor can monitor the ECG signal of those patients through the data sent. Hence, monitoring for potential heart disease is being carried out right in the real-time. In figure 22 shows, the hardware implementation from the beginning of storing the signal, then compressing it using the DWT and finally sending it by the MQTT server. During transmission, the energy consumed is recorded at different levels of scale and frequency by the current sensor. The main procedures for monitoring data by the control contract to the webpage are also detailed down.

- Using the io.adafruit of the IoT cloud, the webpage can show topics related to ECG monitoring.
- The ECG monitoring node MCU publishes data to the MQTT server on a certain topic. These data are forwarded to all the webpages that have subscribed to the same topic.
- ECG data are stored in the database managed by the storage server.

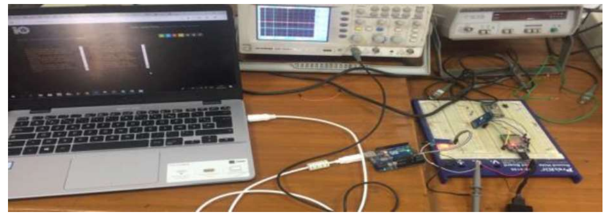

Fig.22 Laboratory implementation of the system

B) Practical Results

The energy consumption in our implementation is an important saving battery in real-time. By observing the ECG signal, energy consumption is presented through different types of filters. Therefore, the sample of 117.dat original signal will be sent that taken up a large of the battery energy. The consumption energy is shown in figure 23 (a) while sending the original signal.

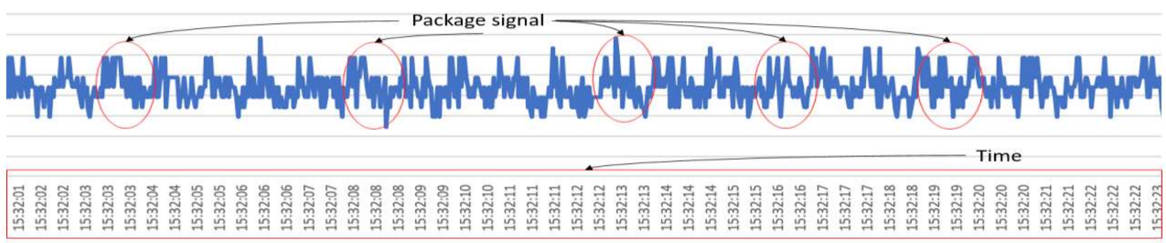

Fig 23 (a): energy consumption for the original signal

After the data, the compressing stage is presented in part (a). The consumption energy is shown in figure 23 (b) while sending the compressed signal. The low pass filter is sent to show consumed power through battery.

The ECG signal compress is observed as a noise-free signal and can be used for further analysis of the disease prediction.

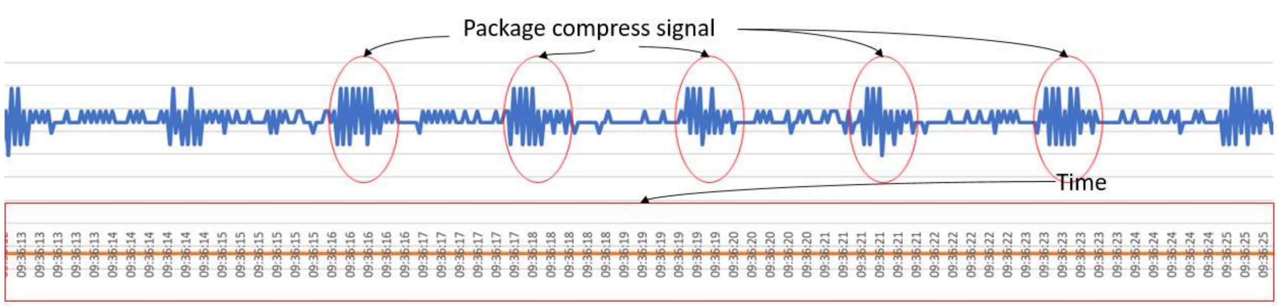

Fig 23 (b): energy consumption for compress signal

As shown in figure 23(a) the 117.dat signal is consumed a large part of the charging of battery during the sending process. But in case, the compressed signal is sent. It will be taken a small part of the battery charger shown in Figure 23 (b). This is achieved in a real-time, low power consumption, low size, and Fast time during the transmission process. As the scale of the wavelet filters increases, the frequency of the output signal decreases with low power consumption of the battery. Hence, in this implementation, according to the different types of wavelet filters frequencies will be used. Therefore, the consumption energy readings are different due to the different wavelet filters scale.

Hence, in this implementation, according to the different types of wavelets have been used. The energy readings consumed from the battery differ due to the different wavelet filters scale.

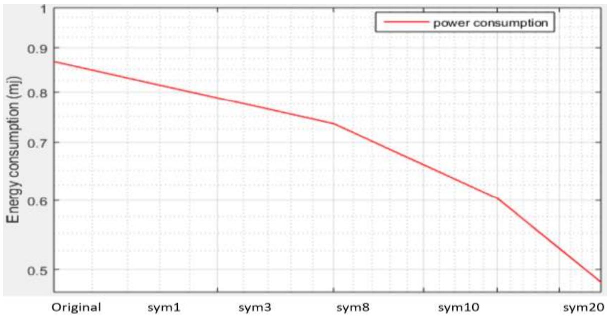

Fig .24 ratio of consumption of power from battery

As shown in figure 24, According to increasing the wavelet filter scale, the wavelet filter frequency is decreased. During frequency decreases, power consumption is decreased. The symlet 20 wavelet filter is achieved as the best type of filter for saving power. However, energy consumption was be decreased by about 13.2% of the battery. So, the analysis of the discrete wavelet transform is important in saving battery power.

V. Conclusion

This paper aims to implement the IoT based healthcare monitoring system. It has been implemented with IoT devices and displayed by using the MQTT server. It is achieved with the database by using a discrete wavelet transform method. This method is very easy to know the health data for patients. This is achieved in real-time, low power consumption, low size, and low cost. As the scale of the wavelet filters increases, the frequency of the output signal decreases with low power consumption of the battery. The Compression outcomes of the proposed sym 20-filter technique are better than the other wavelet filters. The proposed technique gives the high compression ratio, high signal to noise ratio and very less PRD. The features of the original ECG signal are better preserved through the reconstructed signal.

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