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Simulation for Design the Compressed ECG Signal Transmission System with Baseline Wander Noise

Ali Abdrhman Ukasha
Electrical and Electronic Engineering Depatment
Wadi-Alshaatti University
Brack, Libya
a.ukasha@wau.edu.ly

Mousa Hasan Omar
Electrical and Electronic Engineering Depatment
Wadi-Alshaatti University
Brack, Libya
m.omar@wau.edu.ly

Mabrouka Idrees Fadel
Electrical and Electronic Engineering Depatment
Wadi-Alshaatti University
Brack, Libya
m.fadel@wau.edu.ly

***Abstract*— An electrocardiogram (ECG) signal is a representation of the electrical activity generated by the heart muscles that is primarily used to detect heart abnormalities. Due to the sensitive nature of the ECG, it contains many types of noise such as baseline wandering, powerline interference, EMG signal, and electrode motion artifacts. This paper introduces a simple signal processing techniques to remove baseline wandering noise from ECG signal. Baseline wandering is a low-frequency noise ranging from 0.5 to 0.6 Hz. This paper proposes a Notch filter and an orthogonal wavelet family by Daubechies families to reduce baseline wandering from the ECG signal. In this work, the ECG compression is based on discrete cosine transform (DCT) and Run Length Encoding (RLE). A comparative study for system performance of the ECG signal in terms of compression ratio (CR), percentage root mean square difference (PRD), mean square error (MSE), and peak-signal-to-noise ratio (PSNR). The results showed that only 12% of the DCT coefficients after the compression process are used to reconstruct the ECG signal, with a compression ratio up to 8.6957 by using (RLE) encoding. Percentage root mean square difference is 0.1436 (PRD) after filtering the signal with a low-pass FIR at the PSNR is equal to 31.0157dB at the end point of the receiver.**

Keywords—ECG signal; DCT & DWT transforms; Zonal sampling; Run Length Encoding; Baseline wander noise; Notch & FIR filters

I. INTRODUCTION

The ECG noise removal has been a subject of fascinating study. The purpose of the de-noising filtering process is to reduce the noise level of the signal, and at the same time, to prevent distortion of the waveform. This last property is of vital importance so that no misdiagnosis or analysis of the ECG signal is made. Noise removal is a fundamental problem in signal processing [1]. The electrocardiogram (ECG) is a vital medical tool for the diagnosis of heart disease. Electrocardiogram is a safe, harmless and rapid technique for diagnosing cardiovascular diseases. The accuracy of the information extracted from a signal requires an appropriate characterization of the waveform profiles and that it is not contaminated by noise. However, an ECG is a rather weak electrical signal, and its amplitude is usually in the millivolt level. ECG noise includes interference from the device itself, background wandering, human activities, and other factors in the signal. Baseline wandering is the most common noise in ECG signals, which has the greatest overlap in its amplitude. It usually causes the signal to deviate from the normal baseline level, affecting the ST segment, and small waves such as P wave, T wave, etc. The changes of these morphological waves can seriously interfere with the diagnosis of the disease.

The main reason for baseline wandering is the effect of breathing Compared with ECG signals, baseline wandering is low-frequency noise, with a frequency of 2 ~ 0.05Hz The frequency range of the ECG signal is between 100 0.05Hz and voltage levels of 4-0.5 mV team noise EMD is one of the main noises [2]. The frequency range is from 1 to 10,000 Hz and the voltage levels are from 0.1 to 10 millivolts, depending on the rate of movement and stress of the muscles. The EMG signal thus distorts the ECG signal and causes random noise in it. , the ECG signal spectrum overlaps with the ECG signal spectrum and thus it is difficult to distinguish between ECG signal peaks and noisy signal peaks caused by patient movement. The presence of unwanted interference causes a serious problem in ECG diagnosis. When an ECG signal is obtained, it is usually contaminated because there are so many sources of noise that it is difficult for a specialist to read it [3].

Inside the spectrum of the noise signal with the spectrum of the ECG signals is a big problem facing doctors, and then it is difficult to distinguish between the peaks of the ECG signal and the peaks of the noise signal accompanying the signal. This causes unwanted interference in the signal and is a serious problem in diagnosing the ECG signal. This noise creates obstacles for doctors in order to make a true diagnosis, therefore, it must be removed from the ECG signal by using the correct methods of signal processing and extracting the pure ECG signal. The problem lies in the possibility of reconstructing the ECG signal associated with the compressed and encoded baseline wandering noise at the receiver with high quality.

This paper aims to filter the signal associated with heart noise (baseline wander) and transmit it in a lower size (compressed and encoded) and receive it in high quality so that the cardiologist can better understand and diagnose it.

II. METHODOLOGY

The proposed method for designing the system depends on three stages: The first stage is signal preprocessing stage (as shown in Fig. 1), and the second stage is signal compression (as shown in Fig. 2).

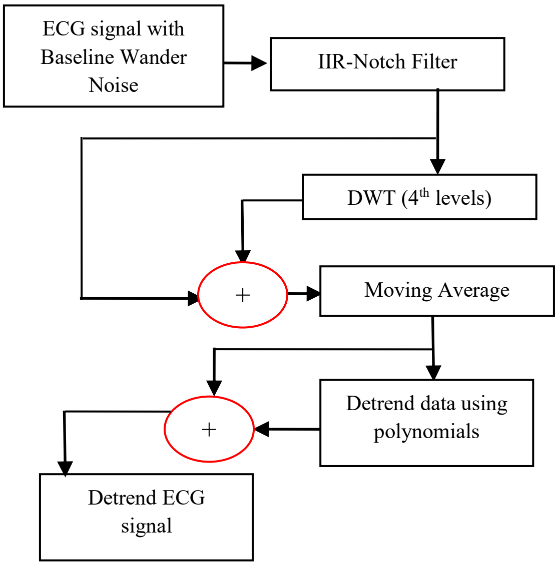


Fig. 1. Flowchart of the ECG signal preprocessing stage

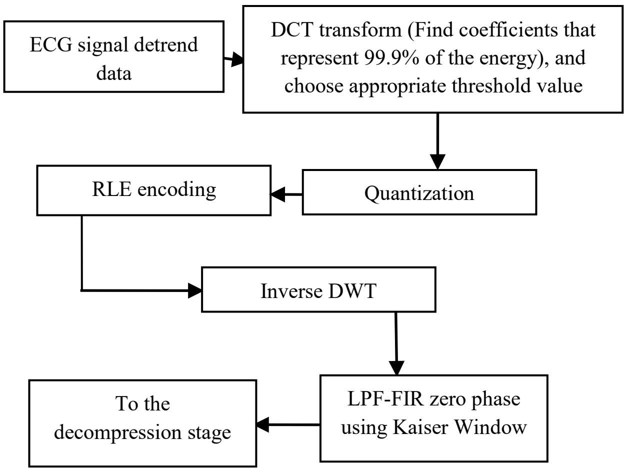


Fig. 2. Flowchart of the ECG signal compression stage

III. LITERATURES REVIEWS

Nine widely used methods are introduced for eliminating BLW were implemented, namely: interpolation using cubic slices, filter, FIR filter, IIR, mean square, mean filter, median filter. Animated, independent component analysis, interpolation and successive subtraction of average values in the interval, RR experimental mode dissociation and wavelet filtering. The best results were obtained using the FIR high-pass filter method with a cut-off frequency of 0.67 Hz [4].

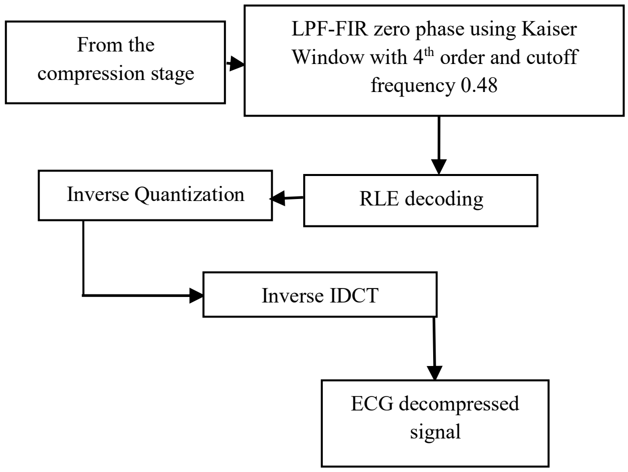


Fig. 3. Flowchart of the signal compression stage

Kaur et al, presented the implementation and evaluation of different methods for removing this noise. The power spectral density (PSD) and the average power and signal-to-noise ratio (SNR) of the signals are calculated to compare the performance of different filtration methods. IIR zero phase filtering has proven to be an effective method for removing baseline wandering from the ECG signal. Results were completed using Matlab software and the MIT- BIH arrhythmia database [5].

Uzzal Biswas et al, proposes orthogonal wavelet family by investigating different wavelet families to reduce baseline wandering from ECG signal. The analysis based on performance parameters justified that the proposed bio-orthogonal wavelet family is a performance better for reducing baseline wandering from the ECG signal than adaptive NLMS filters and slit filters [6].

A transformation-based methodology was introduced for ECG signal compression. The results of the included simulations demonstrate the effectiveness of these transforms in biomedical processing signals. When compared, the discrete cosine transform and the fast Fourier transform give a better compression ratio, while the discrete wavelet transform produces good resolution coefficients with a low ratio [7].

A new approach to run-length coding (RLE) was proposed to compress discrete cosine transform (DCT) coefficients of ECG signals in the time domain. The power compression feature of a DCT simplifies length encoding by grouping related coefficients into discrete segments. The results indicate that for record 117 of the arrhythmia database, MIT The proposed BIH-compression algorithm can achieve a compression ratio of 14.87 at a bit rate (185 bps) [8].

IV. ELECTROCARDIOGRAM SIGNAL

Electrocardiography is the process of producing an electrocardiogram (ECG), or recording of the heart's electrical activity, which is a graph of voltage against time of the heart's electrical activity using electrodes placed on the skin. These electrodes detect small electrical changes that result from depolarization in the heart muscle followed by repolarization During each cardiac cycle (heartbeat), changes in the normal

ECG pattern occur in many heart disorders, including abnormal heart rhythms (such as atrial fibrillation and ventricular tachycardia), and insufficient blood flow in the coronary artery (such as ischemia). Myocardial infarction (myocardial infarction), and electrolyte disturbances (such as hypokalemia and hyperkalemia). Traditionally, “ECG” usually means a 12-lead electrocardiogram taken during placement. Other devices can record the electrical activity of the heart such as the Holter monitor, but also some Smart watch models are capable of recording an EKG ECG signals can be recorded in other contexts using other devices ECG test records. Electrocardiogram or ECG It is a simple test to check the heart rhythm, as sensors or electrical paths are placed for a few minutes over the chest, arms and legs, which detect the electrical signals emitted by the heart, and the cardiologist examines them to see if there is a defect in them. ECG differs from an echocardiogram, which is an examination of the heart (in English: Echocardiogram). Natural electrical impulses coordinate the contractions of the different parts of the heart. Changes in the electrocardiogram may be an indication of the presence of certain medical conditions affecting the heart [4]. Figure (4) shows the main waves that appear on the ECG results. There are five main waves that appear on the results of the electrocardiogram "P, Q, R, S, T", respectively, where each wave symbolizes a specific point in the heart when the electric current flows in it, starting from the atrium to the ventricle, and the periods between the waves symbolize the time that the current needed to reach point to point [9]. Figure (4) shows the most important part of an ECG, the complex (QRS) whose shape and time of occurrence give many statistics and details about heart function [3].

A typical QRS detection algorithm generally consists of two phases: preprocessing and decision. Inclusively, the first involves a kind of filtering [10]. While the latter attempts to locate QRS complexes in an ECG signal.

V. Baseline Wander Noise

Baseline wandering is the effect in which the fundamental axis (x-axis) of a signal appears to be "wandering" or moving up and down rather than being straight. This shifts the entire signal from its natural base. In the ECG signal. Baseline wandering is caused by improper electrodes (electric skin resistance) and patient movement and breathing. Figure 5 shows a typical ECG signal affected by baseline wandering. The frequency content of baseline wandering is on the order of 0.5 Hz. However, increased body movement during exercise or a stress test increases the frequency content of baseline wander noise, since the baseline signal is a low-frequency signal [1].

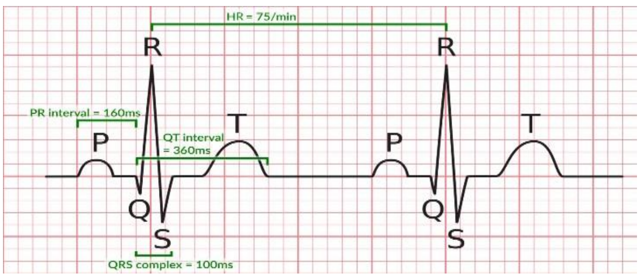


Fig. 4. ECG signal

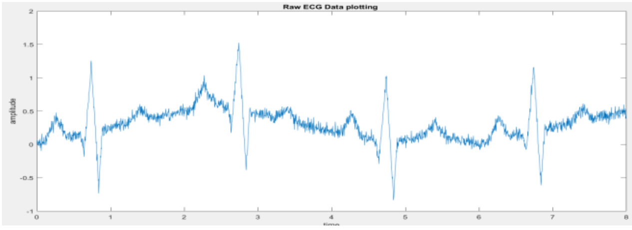


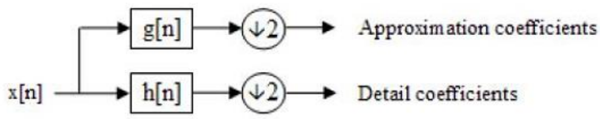
Fig. 5. ECG signal with Baseline wander noise

VI. Data Compression

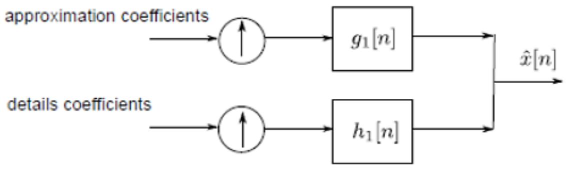
In signal processing, data compression, source coding or bit rate reduction is the process of encoding information using fewer bits than the original representation i.e. compression given either lossy or lossless. Lossless compression reduces bit by limiting and shortening the statistical frequency [1], where no information is lost in lossless compression. Compression is usefull, because it reduces the resources required to store and transmit data [12].

VII. Discrete Wavelet Transform (DWT)

Wavelet analysis methods were developed by Y. Meyer in 1985, and Daubechies worked on finding orthogonal wavelets with compact support in 1988. Stephane Mallat in 1989 developed the basic algorithm for applying discrete wavelet transform by using filters. And in the year 1990, wavelets were used in the mathematical and engineering fields, as Nathalie Delprat's provided an explanation in the time-frequency domain of the continuous wavelet transform in 1991, and found the wavelet packet transform [13]. The basic difference between continuous wavelet transform and discrete wavelet transform is that it is possible to choose a subset of the necessary gradations and transitions in the processing process, instead of performing the conversion on all the gradations and transitions by performing time interrupts in the signal, and this conversion results in a sufficient amount of information so that it is The computation time is little while preserving the basic information of the signal [14]. There is an efficient way to apply this transformation using filters, and it was developed by (Mallat) in 1988 where the signal x[n] is divided into a low-pass filter g[n] to get the coefficients Approximate coefficients, which are usually known as scaling coefficients, which represent the low-frequency and high-gradient signal components on a high-pass filter h[n] to obtain the detailed coefficients, which are usually known as wavelet coefficients, which represent High-frequency and low-scale signal components [14]. This division allows analysis of the signal within different frequency bands with different resolutions as shown in Fig.6.



(a)



(b)

Fig. 6. (a) Signal analysis using down-sampling, and (b) Signal synthesis using up-sampling

The wavelet transform family contains many types, such as: Haar, Coiflet, Symlet, and Daubechies which are used in this paper. Daubechies family is symbolized by the symbol (dbN), where N indicates the order of the wavelet, as shown in the Fig. 7.

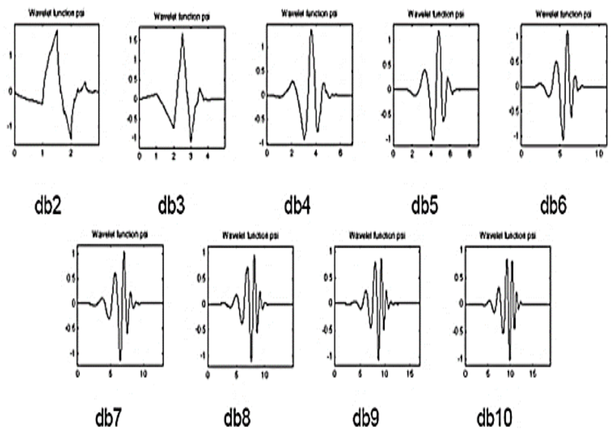


Fig. 7. Daubechies family wavelets

VIII. DISCRETE COSINE TRANSFORM (DCT)

The discrete cosine transform (DCT) helps to separate the signal into spectral sub-bands of different importance. It is similar to the discrete Fourier transform, it transforms the signal from the spatial domain into the frequency domain. The transformation allows decoupling between the input components to make them independent, which allows for more efficient encoding and thus an increase in the compression ratio [15].

IX. RUN LENGTH ENCODING (RLE)

RLE works by reducing the normal size of a repeated string of symbols. The subscripted strings will then be pointed to by a pointer. Then the view known as byte padding must be used in order to enable the decoder to differentiate between the pointer and the symbol that returns to the data stream [16].

X. DISCUSSION AND RESULTS

The used heart pulse signal that contains baseline wander noise is shown in Fig. 8. Figure (9) represents the output of the notch filter to remove the base line noise. An ECG signal associated with the baseline noise and the filtered signal (baseline wander noise removed) are shown in Fig. 10.

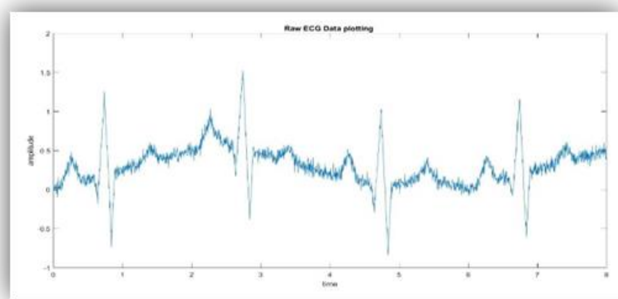


Fig. 8. ECG signal with baseline wander noise

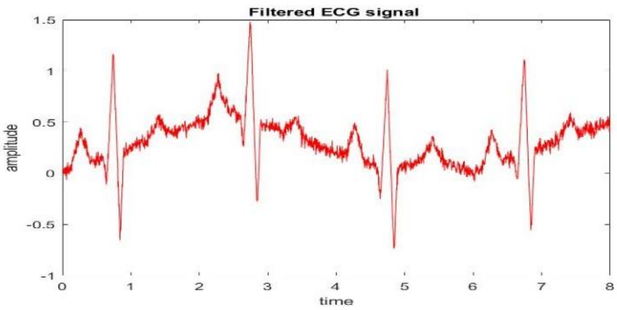


Fig. 9. ECG signal filtered by Notch filter

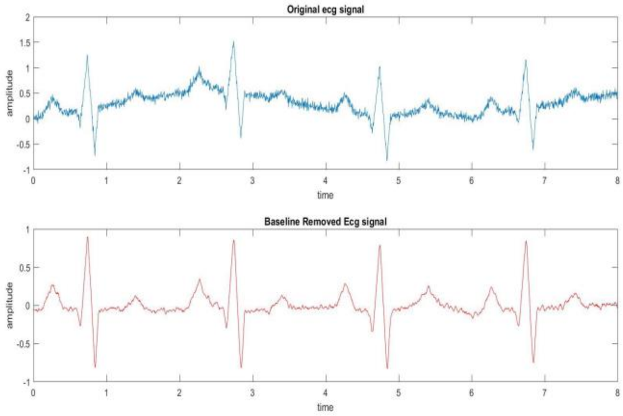


Fig. 10. Original ECG signal and after Baseline wander noise removed

Figures (11 and 12) shows the signal values after discrete wavelet analysis. The two figures show the analysis in the first, second, third and fourth levels of wavelet analysis, respectively. We selected the 99.9% of the ECG signal energy filtered. This work show that the percentage of coefficients that represent the signal after the compression process is equal to 12% of the total coefficients for the signal. Figure (13) shows the difference between the original signal and the compressed signal. Figure (14) shows the output of the reconstructed signal in the compression stage using discrete cosine transform (DCT) and the error between the original and the reconstructed signal.

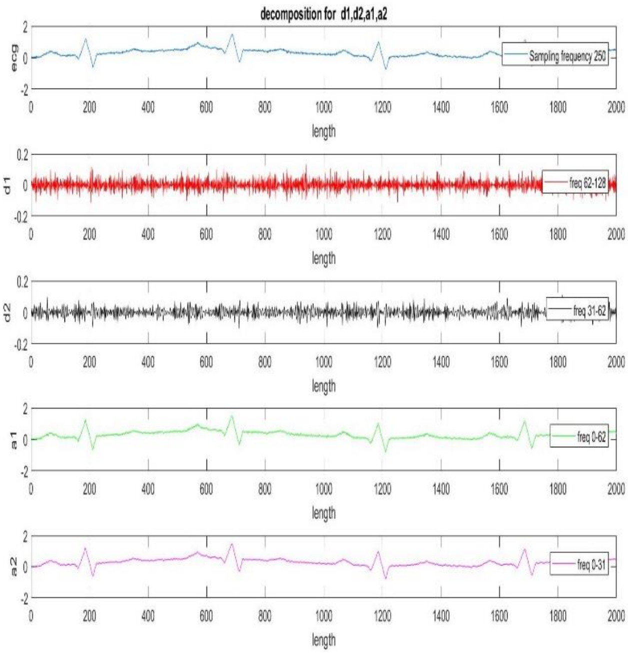


Fig. 11. Discrete wavelet analysis in the first and second levels

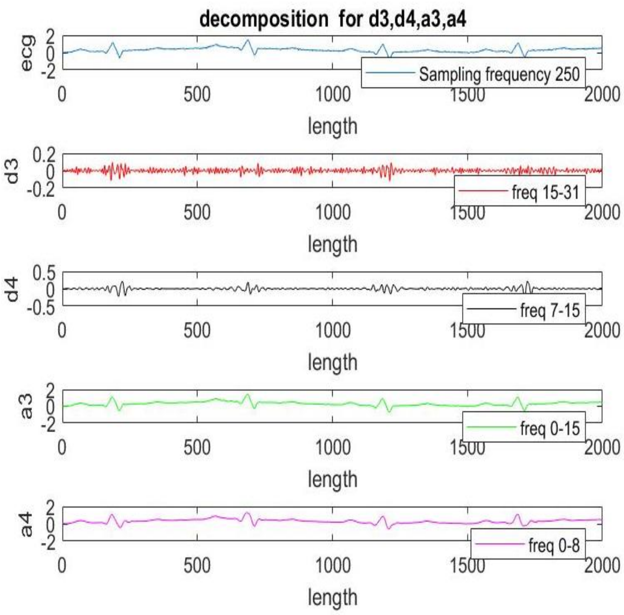


Fig. 12. Discrete wavelet analysis in the third and fourth levels

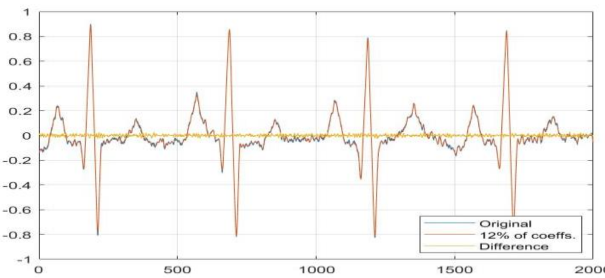


Fig. 13. Original ECG and ECG compressed signals

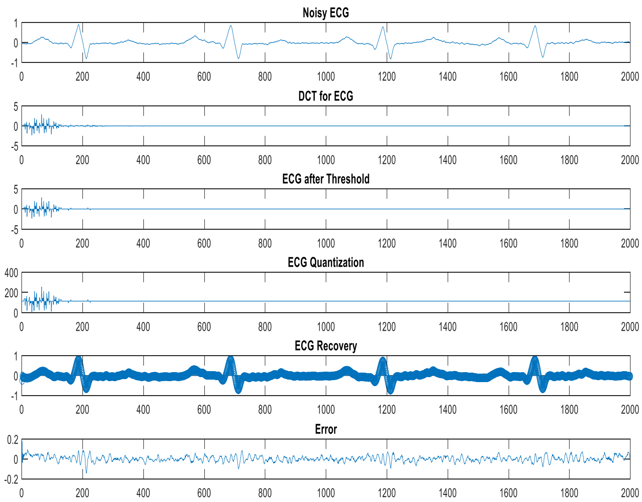


Fig. 14. The Operations that applied to the signal in the compression stage

Figure (15) shows the reconstructed signal after the compression and decompression processes when a threshold value equals to "0.22" is applied to the ECG signal. Figure (16) shows the relationship between Daubechies wavelet in terms of SNR, PRD, and PRD1.

where: CR: Compression ratio, PRD is percentage root mean square difference for ECG signal reconstruction at the receiver, PRD1 is percentage root mean square difference ECG signal reconstruction after filtering, SNR is signal-to-noise-ratio for ECG signal after decompression and decoding.

The experiments proved that the LPF-FIR filter, with a degree of 70, obtain the best results in terms of signal-to-noise ratio (SNR) and percentage root mean square differences (PRD) for ECG signal reconstruction. The db6 wavelet was chosen for being the best in signal analysis and coefficients reconstruction compared to the remains of the wavelets. Figure (17) shows the relationship between the coefficients representing the signal and the PSNR and SNR measures. Table I summarizes the results of the values of the wavelets that were chosen in the paper and their relationship to the standards that were chosen in this paper. Where the results showed that the db5, db6 and db40 wavelets gives the best results in terms of peak-signal-to-noise ratio (PSNR), percentage root mean square differences (PRD) and compression ratio CR.

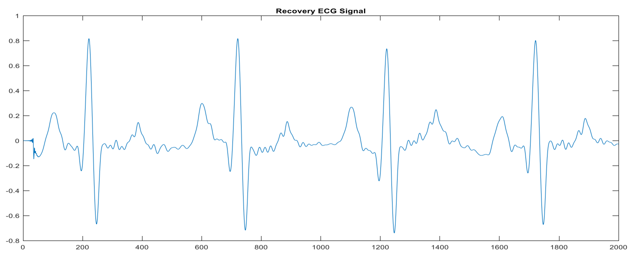


Fig. 15. Reconstruction ECG signal after decompression stage

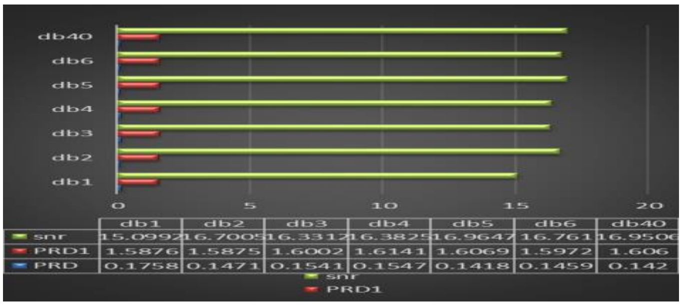


Fig. 16. The relationship between the SNR, PRD versus Daubechies wavelets

This study showed that when choosing 99.9% of the total energy signal, the coefficients that represent the signal are 12% and the compression rate was 3.5%.

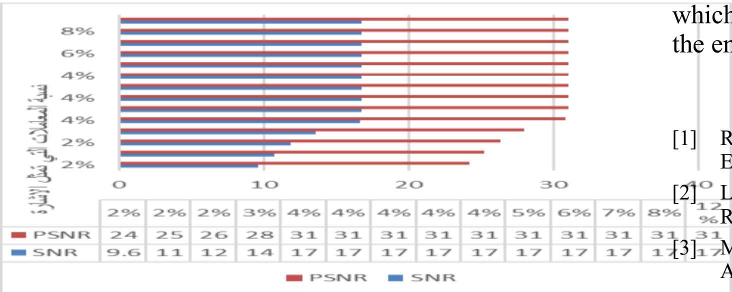


Fig. 17. The coefficients number that represents the signal versus the PSNR and SNR measures

TABLE I. RESULTS OF SNR, CR , AND PRD FOR ECG SIGNAL

	CR_Th	RC	PRD	PRD1	Peaksnr1r	PR2D	Peaksnr2r	Snr
db1	4.0000	8.2645	0.1758	1.5876	9.9702	0.1734	29.2049	**15.0992**
db2	3.5500	8.6957	0.1471	1.5875	10.0957	0.1446	30.9049	**16.7005**
db3	3.4000	8.7719	0.1541	1.6002	10.0758	0.1509	30.5859	**16.3312**
db4	3.2500	9.0909	0.1547	1.6141	10.1035	0.1499	30.7452	**16.3825**
db5	3.5000	8.6957	0.1418	1.6069	10.0981	0.1404	31.2721	**16.9647**
db6	3.5000	8.6957	0.1459	1.5972	10.0905	0.1436	31.0157	**16.7610**
db40	3.5000	8.6957	0.1420	1.6060	10.0992	0.1406	31.2531	**16.9506**

XI. CONCLUSIONS

The quality of the reconstructed signal is one of the most important metrics used in many signal processing, compression and encoding applications, where the reconstructed signal obtained small difference between it and the original signal in terms of the signal recombination measure known as the PRD distortion measure. The study proved that the Daubechies wavelet is useful in analyzing the signal and reconstructing it using DWT transform, and at Db6 we obtained a high signal quality, as the ratio of the PSNR scale value reached 31.0157 decibels (dB). This paper concluded that when choosing 99.9% of the signal energy, the percentage of DCT coefficients that represent the signal was 12%, and the compression ratio was 3.5%. The percentage of coefficients decreases whenever the selected value that represents the signal decreases when compressed, as the coefficients that represent the signal reach 2% when choosing 95% of the signal energy and the compression ratio is 1.75%. The results show that the best value for the threshold is 0.22, and the best order for digital filter was 70. In this paper, we pre-processed the signal and sent it as compressed and encrypted, and received it correctly after reconstructing, decompressing, decoding, and filtering, which gave good results. The quality of the received signal at the end point is with a value equals to 31.0157 db.

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