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FUZZY BASED PSO SCHEME FOR ECG SIGNAL DENOISING(ECG)

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ABSTRACT:

ECG (electrocardiogram) is a test that measures the electrical activity of the heart. An efficient and low power VLSI implementation of compression algorithm has been presented in this concept. To improve the performance, the proposed VLSI design uses bit shifting operations as a replacement for the different arithmetic operations. ECG compression algorithm comprises two parts: an adaptive linear prediction technique and content-adaptive Golomb Rice code. Further this project is enhanced by Fuzzy-based PSO technique. Proposed coding is efficient technique which allows a compact representation of data by electively reducing the error between the data itself and information “predicted” from past observations. The prediction techniques build an estimate x'(n) for a given sample x(n) of the signal by using past two samples with low power and less area.

1. INTRODUCTION:

Fetus health condition is monitored by many methods where Electrocardiography is one of the frequently used methods which shows the fetus heart’s electrical activities. Generally, an invasive or non-invasive method of recording of Fetal ECG (FECG) is performed. In invasive method of recording, the electrode has to be placed on the scalp of the fetus to measure the ECG but the electrode has to be passed through mother’s womb which creates difficulties to the mother [1] and also possible only at the later stage of pregnancy period. The non-invasive method of recording does not provide any trouble to the mother because the electrode has to be placed on mothers’ abdomen to measure the ECG of the fetus. There are several approaches proposed to record the fetal ECG under non- invasive method which uses either a single lead or two leads or multiple leads. For a single lead method of recording, only one electrode is positioned on the mothers’ abdomen, two lead systems uses two electrodes which have to be positioned on the chest and abdomen and multiple lead systems require multiple electrodes to record the fetal ECG. There are several complications in non-invasive method of recording fetal ECG, because the recording is not directly taken from the fetus which is measured on the abdomen, hence the fetal ECG is to be extracted from signal contaminated by multiple sources of interferences. Apart from these sources of interferences the low signal level of fetal ECG [2] and the spectral overlapping of mother ECG and fetal ECG [3] makes the extraction more critical. ECG (electrocardiogram) is a test that measures the electrical activity of the heart. The heart is a muscular organ that beats in rhythm to pump the blood through the body. In an ECG test, the electrical impulses are generated while the heart beatings are

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recorded. The extensive use of digital electrocardiogram (ECG) produces large amounts of data. Since it is often necessary to store or transmit ECG records, efficient compression techniques are important to reduce transmission time or required storage capacity. Especially critical are long duration (24 or even 48 hours) Holter exams. The data generated in such cases can surpass 1G bytes. These Holter devices must present good storage capacity, in addition to reduced dimensions and low power dissipation in order to be comfortably carried by patients. These facts show the importance of using some data compression method that preserves the essential characteristics of the original signals. In recent years several ECG compression methods have been discussed and average compression ratios (CR) ranging approximately from 2:1 up to 50:1 have been reported [6], [7], [8]. recent years, Cardiovascular disease (CVD) has been the major cause of death worldwide and is reported as roughly 31% of all global deaths [1]. To diagnose this disease and many others, the electrocardiogram (ECG) signal is used. ECG signal is a biomedical signal containing useful information about the heart condition and it is the most common screening tool for cardiac disease diagnosis. In a 24-hour ECG signal monitoring system, the monitoring system will be producing a huge amount of data. To understand the amount of data generated during ECG monitoring process, following two different frequencies can be taken as examples. Normally at the sampling frequency of 125 Hz, 7.5 KB of ECG data is generated for the duration of 1 minute per sensor. If the sampling rate is 500 HZ then it will generate 45 KB of data per minute for one sensor [2]. So, to store this huge data, a solution is required to reduce the data of ECG signal. For a solution, ECG compression is performed in such case to save storage space. Cardiovascular diseases (CD) have become the top cause of death globally in recent years, responsible for over 31% of all global deaths annually [1]. Reading electrocardiogram (ECG) signal is the most commonly used method to monitor heartbeat. This biomedical signal is widely used in medicine as a screening tool for cardiac disease diagnosis. It has various components such as waves, segments and intervals. A typical ECG signal is shown in Fig. 1 [2]. The precautionary benefits of ECG data are limited due to their low availability. Long-term ECG recording is often carried out with patients admitted with cardiac problems. ECG can also be recorded continuously for 24-48 hours using monitors for mobile patients [3]. Thus, a large amount of data is collected using continuous ECG monitoring systems over such periods. In order to reduce the amount of data, a real-time data compression algorithm which can save storage space is needed.

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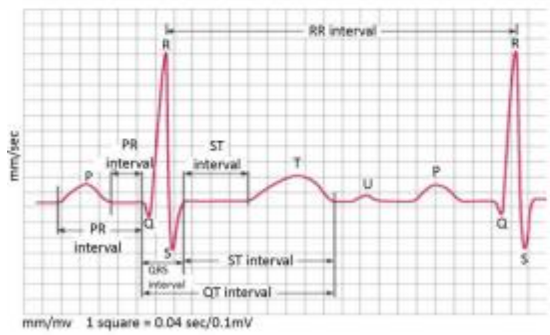

Three types of compression techniques are used on ECG data [4] (Fig. 2). 1) The direct data method uses the data in time domain for compression. Several well-known direct data techniques are used, including delta pulse code modulation (DPCM) [5, 6], turning point (TP) [7], amplitude zone time epoch coding (AZTEC) [8, 9], coordinate reduction time encoding system (CORTES) [10], the delta algorithm and Fan algorithm [11]. 2) The transformed method converts the time domain into a frequency domain; the key idea is based on energy redistribution. Traditionally, Fourier transform, Fourier descriptor [12], Karhunen-Loeve transform (KLT) [13], Discrete cosine transform (DCT) [14, 15] and Wavelet transform [16, 17] have all been widely used. Some new ideas, such as compressed sensing, are still based on this method [18]. 3) The parameter extraction method extracts the dominant features from the raw signal; others developed include the peak picking and prediction method [19], and the neural-based or syntactic methods [2]. In general, the compression method applied in the ECG signal includes lossless compression and lossy compression. Although lossy compression techniques deliver greater compression performance, they are not accepted by medical regulatory bodies.

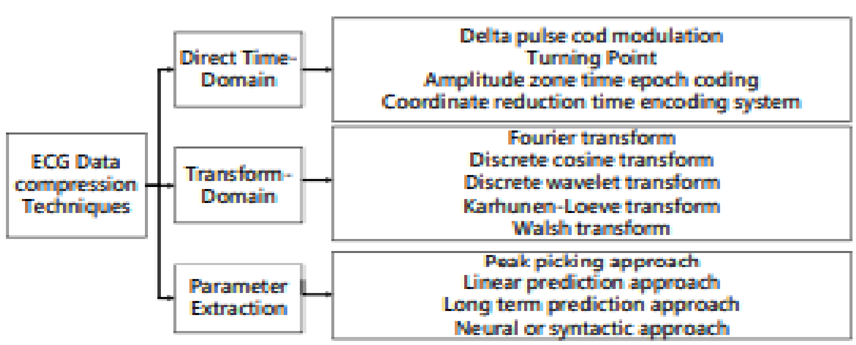

FIGURE. 2 The overview of ECG compression technique

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2. LITERATURE SURVEY:

Time sequenced adaptive filtering has been recommended by Ferrara & Widrow [4] for FECG enrichment. They identified the non-stationary fetal ECG signal having recurring statistical characteristics. The Least Mean Square (LMS) adaptive filter can able to follow up such fast changing non stationarities, hence an adaptive filter have to be designed with rapidly varying impulse response to improve the performance of the extraction. The method uses many sets of hyper parameters to adapt for fast changing impulse response. In order to adapt for fast changing impulse response, the method requires more abdominal signals and also timely identification of estimated fetal pulse. Apart from the above requirements the technique needs prior information of fetal ECG positions. The time sequenced adaptive filtering provides more accurate results compared to classical LMS adaptive filter. The overall performance of the adaptive filter is increased when the number of channel input is increased. The main advantage of this approach is that the prior knowledge of signals' power spectrum is not required. But, the time sequenced method need the estimation for the timely identification of the pulse, to synchronize the filter regeneration and the fetal cardiac cycles. They stated the future direction to enhance the results by finding better method to locate the fetal pulse positions in order to make this approach with recordings having lower SNR. Kam & Cohen [5] identified a method to find the fetal ECG using Infinite Impulse Response (IIR) filtering technique and Genetic Algorithm (GA). The hybrid IIR-GA approach on fetal ECG extraction, the adaptation rule is combined with GA, whenever the estimated gradient stuck with local extremum. Hybrid IIR-GA provide best with simulation compared to FIR LMS based method but with real data, the method fails to show the significant difference between them. This may be because of the body transfer function acts as a simple low pass filter so that a lower order FIR adaptive filter is sufficient, and the authors suggested further studies are required to analyze this assumptions. Talha et al. [6] also presented similar approach of GA based Finite Impulse Response (FIR) filter for extraction where Genetic algorithm is used as a optimizer for FIR filter and the results are compared with the other approaches of adaptive filters like wiener filter, Recursive Least Mean Square (RLMS) and NLMS filters. The NLMS approach provide better results in terms of reliability and speed of convergence but provide divergence results when the adaptation is too large which have been overcome by the method of GA based FIR filter. GA with eight bits and ten iterations provide better quality compared to other algorithms and an improvement may be provided by changing the order of the filter. The adaptive filtering approach may be combined with other approaches to provide enhancement in extraction. Kholdi et al. [7] identified a GA based adaptive filter which uses LMS based adaptive filter for extracting fetal ECG, where the best filter coefficients are calculated based on genetic algorithm which makes the adaptive filter response converge into global extremum. The random search nature of GA find the optimum filter coefficients even the structure of nonlinear transformation is unknown or the structure may vary for different person. This adaptive process does not need the knowledge in advance about the signal and noise statistics, only assumes the signal is uncorrelated with noise. The input and output SNR are calculated with different delay. Even, changes in the amplitude of the MECG signal and rate of delay, the output SNR does not have much change, along with it provides fast response for extraction of FECG. Niknazar et al. [8] presented an extended Kalman filtering technique to extract FECG. The method utilizes single lead recording and applied nonlinear Bayesian filtering framework for extraction. This Kalman filtering (KF) framework considered as a type of adaptive filter, and provides an impressive method for noise elimination and quality extraction of FECG. Extended Kalman Filter (EKF) with a backward recursive smoothing phase, design the Extended Kalman smoother (EKS). The approach first extracts the dominant ECG and considering other sources are Gaussian signal. Once detecting the predominant component of maternal ECG in the actual signal, then the fetal ECG extraction takes place from the lingering signal. The process is called as sequential EKF and the extended state Kalman filtering linearizes the mean and covariance is named as parallel EKF or EKS where the parallel EKS produce more accurate extraction compared to sequential EKS. This model effectively separates the FECG even if the signal is embedded with mother components and permits to identify R peaks. The sensitivity analysis is performed under dissimilar cases; demonstrate the success of the algorithm.

3. ELECTROCARDIOGRAM:

An electrocardiogram is a picture of the electrical conduction of the heart. By examining changes from normal on the ECG, clinicians can identify a multitude of cardiac disease processes. There are two ways to learn ECG interpretation — pattern recognition (the most common) and understanding the exact electrical vectors recorded by an ECG as they relate to cardiac electrophysiology — and most people learn a combination of both. This tutorial pairs the approaches, as basing ECG interpretation on pattern recognition alone is often not sufficient.

Parts of an ECG

The standard ECG has 12 leads. Six of the leads are considered “limb leads” because they are placed on the arms and/or legs of the individual. The other six leads are considered “precordial leads” because they are placed on the torso (precordium).

The six limb leads are called lead I, II, III, aVL, aVR and aVF. The letter “a” stands for “augmented,” as these leads are calculated as a combination of leads I, II and III.
The six precordial leads are called leads V1, V2, V3, V4, V5 and V6.

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The Normal ECG

A normal ECG contains waves, intervals, segments and one complex, as defined below.

Wave: A positive or negative deflection from baseline that indicates a specific electrical event. The waves on an ECG include the P wave, Q wave, R wave, S wave, T wave and U wave.

Interval: The time between two specific ECG events. The intervals commonly measured on an ECG include the PR interval, QRS interval (also called QRS duration), QT interval and RR interval.

Segment: The length between two specific points on an ECG that are supposed to be at the baseline amplitude (not negative or positive). The segments on an ECG include the PR segment, ST segment and TP segment.

Complex: The combination of multiple waves grouped together. The only main complex on an ECG is the QRS complex.

Point: There is only one point on an ECG termed the J point, which is where the QRS complex ends and the ST segment begins.

The main part of an ECG contains a P wave, QRS complex and T wave. Each will be explained individually in this tutorial, as will each segment and interval.

The P wave indicates atrial depolarization. The QRS complex consists of a Q wave, R wave and S wave and represents ventricular depolarization. The T wave comes after the QRS complex and indicates ventricular repolarization.

ADAPTIVE LINEAR PREDICTION:

ECG signal contains numerous regions with sharp amplitude variations, such as QRS, P, and T wave regions, as shown in Fig. 1, which may result in a higher prediction error during prediction error estimation phase. In [8], an adaptive linear predictor technique is proposed to improve the prediction error by keeping its value minimum.Previous four samples are used to estimate the prediction value, which has been shown in fig. 3. The value of the four parameters i.e.'D1_2', 'D1_3', 'D2_3', and 'D3_4'is calculated through the following

equations;

$$D1\_2\ (n) = x\ (n-1) - x\ (n-2) \quad (2)$$

$$D1\_3\ (n) = x\ (n-1) - x\ (n-3) \quad (3)$$

$$D2\_3\ (n) = x\ (n-2) - x\ (n-3) \quad (4)$$

$$D3\_4\ (n) = x\ (n-3) - x\ (n-4) \quad (5)$$

Taking the characteristics of the ECG signal into consideration, the simple differential predictors with coefficients are used. Due to low complexity computation and

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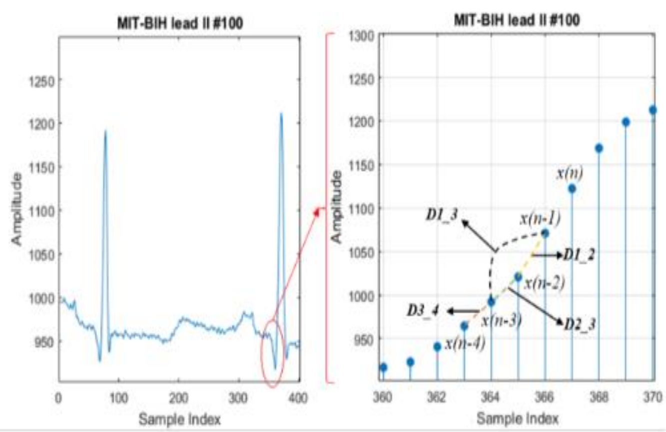

good performance in estimating prediction value, the following three differential predictors have been selected in algorithm development as shown in (6), (7) and (8).

A detailed discussion on the derivation of the equations (2) to (8) can be found in [8]. P1: $\hat{x}(n) = x(n-1)$ (6) P2: $\hat{x}(n) = 2x(n-1) - x(n-2)$ (7) P3: $\hat{x}(n) = 3x(n-1) - 3x(n-2) + x(n-3)$ (8)

4. PROPOSED TECHNIQUE:

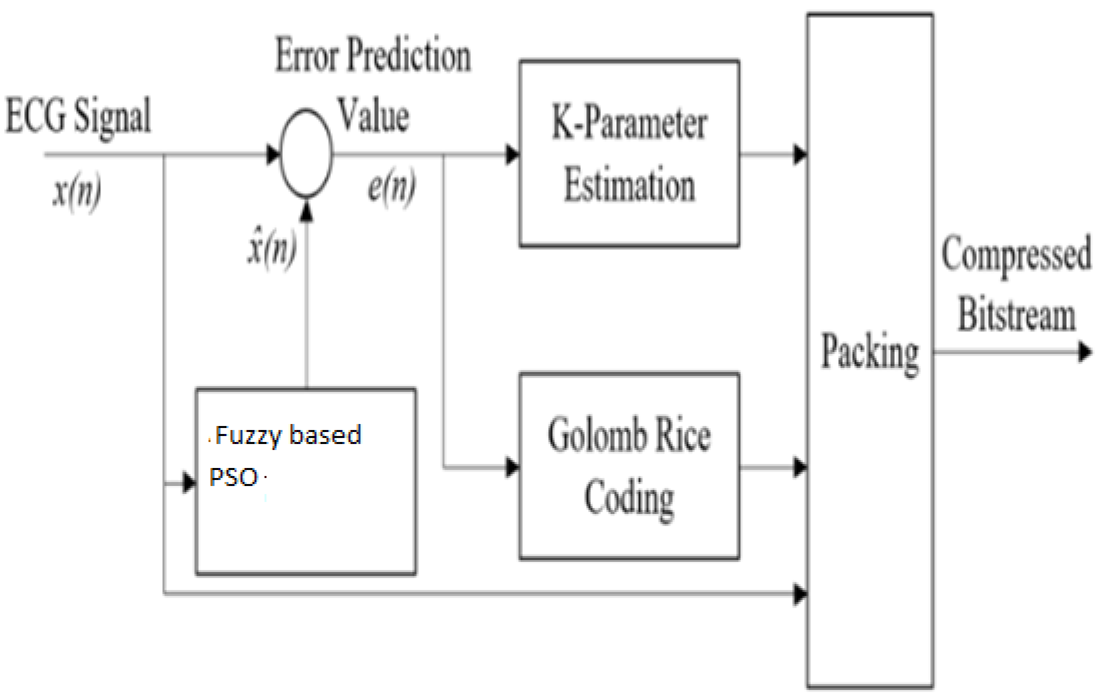

Fig:1. proposed technique

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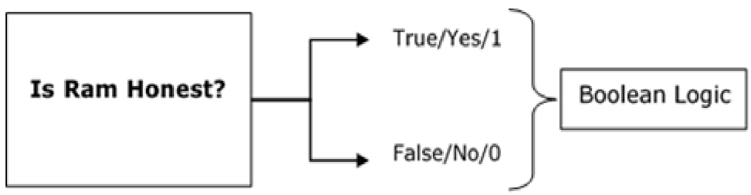
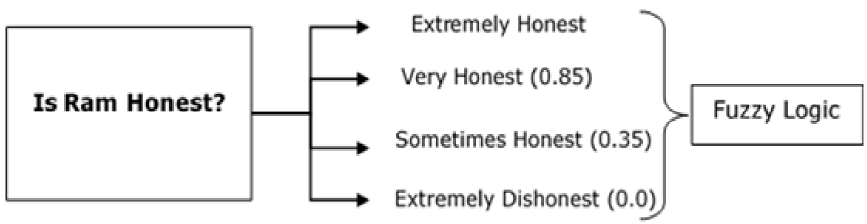
FUZZY LOGIC

Fuzzy Logic resembles the human decision-making methodology. It deals with vague and imprecise information. This is gross oversimplification of the real-world problems and based on degrees of truth rather than usual true/false or 1/0 like Boolean logic.

Take a look at the following diagram. It shows that in fuzzy systems, the values are indicated by a number in the range from 0 to 1. Here 1.0 represents absolute truth and 0.0 represents absolute falseness. The number which indicates the value in fuzzy systems is called the truth value.





In other words, we can say that fuzzy logic is not logic that is fuzzy, but logic that is used to describe fuzziness. There can be numerous other examples like this with the help of which we can understand the concept of fuzzy logic.

Fuzzy Logic was introduced in 1965 by Lofti A. Zadeh in his research paper "Fuzzy Sets". He is considered as the father of Fuzzy Logic.

A set is an unordered collection of different elements. It can be written explicitly by listing its elements using the set bracket. If the order of the elements is changed or any element of a set is repeated, it does not make any changes in the set.

BASELINE DRIFT CAUSED BY THE RESPIRATION:

Baseline wander is a commonly seen noise in ECG recordings and can be caused by respiration, changes in electrode impedance, and motion. Baseline wander can mask important information from the ECG, and if it is not properly removed, crucial diagnostic information contained in the ECG will be lost or corrupted. Therefore, it is vital to effectively eliminate baseline wander before any further processing of ECG such as feature extraction.

The simplest method of baseline wander (drift) removal is the use of a high-pass filter that blocks the drift and passes all main

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components of ECG though the filter. The main components of ECG include the P-wave, QRS-complex, and T-wave. Specifically, the PR-Segment, ST-Segment, PR-Interval, and QT-Interval are considered as the main segments of the ECG. Each of these intervals/segments has its corresponding frequency components, and according to the American Health Association (AHA), the lowest frequency component in the ECG signal is at about 0.05 Hz [1]. However, a complete baseline removal requires that the cut-off frequency of the high-pass filter be set higher than the lowest frequency in the ECG; otherwise some of the baseline drift will pass through the filter. The frequency of the baseline wander high-pass filter is usually set slightly below 0.5 Hz. Therefore, knowing that the actual ECG signal has components between 0.05 Hz and 0.5 Hz, the forementioned simple approach for baseline removal distorts and deforms the ECG signal. In particular, it affects the ST-segment that has very low frequency components. Furthermore, ectopic beats occurring in the ECG during the course of different types of diseases and injuries change the frequency spectrum of both the baseline wander and the ECG waveforms. All the above-mentioned characteristics demand a more comprehensive approach that works for a wider range of applications and avoids distorting the main ECG waves when removing the baseline drift.

Digital filters are commonly employed method to eliminate baseline wander. Cut-off frequency and phase response characteristics are two main factors considered in the majority of these designs. The use of linear phase filters prevents the issue of phase distortion [2]. For finite impulse response (FIR) filters, it is rather straightforward to achieve linear phase response directly. Feed-forward and feed-back technologies such as infinite impulse response (IIR) filters can also provide minimum phase distortion [3]. In all of these methods, the cut-off frequency should be chosen so that the information in the ECG signals remains undistorted while the baseline wander is removed, which results in a trade-off. Usually, the cut-off frequency is set according to the slowest detected (or assumed) heart rate. However, if there are ectopic beats in the ECG signal, it is even more difficult to find this particular frequency. It is a prevalent phenomenon that the overlap between the baseline wander and low frequency components of the ECG compromises the accuracy of the extracted features.

Time-variant filters are designed to increase flexibility in the adjustment and control of the cut-off frequency. In such methods, the cut-off frequency of the filter is controlled by the low frequency characteristics of the ECG signal [4]. Cubic spline curve fitting [5], linear spline curve fitting [6], and nonlinear spline curve fitting [7] belong to another family of filters that remove the baseline wander but often require some reference points. For instance, the linear spline curve fitting method [5] forms a subsignal of the ECG for a single cardiac cycle starting 60 ms before the P-wave and ending 60 ms after the T-wave and fits a first order polynomial to this sub-signal after

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subtracting the mean of sub-signal. Multirate system wavelet transform has also been utilized for the ECG baseline wander removal. The approach using wavelet adaptive filter (WAF) [8] consists of two steps. First, a wavelet transform decomposes the ECG signal into seven frequency bands. The second step is an adaptive filter that uses the signal of the seventh lowest frequency band as the primary input and a constant as a reference unit for filtering. Another multi-rate system, empirical mode decomposition (EMD), has also been adopted to eliminate the baseline wander. Compared with the wavelet technique that uses some predefined basis functions to represent a signal, EMD relies on a fully data-driven mechanism; that is, EMD does not require any a-priori known basis.

5. RESULTS:

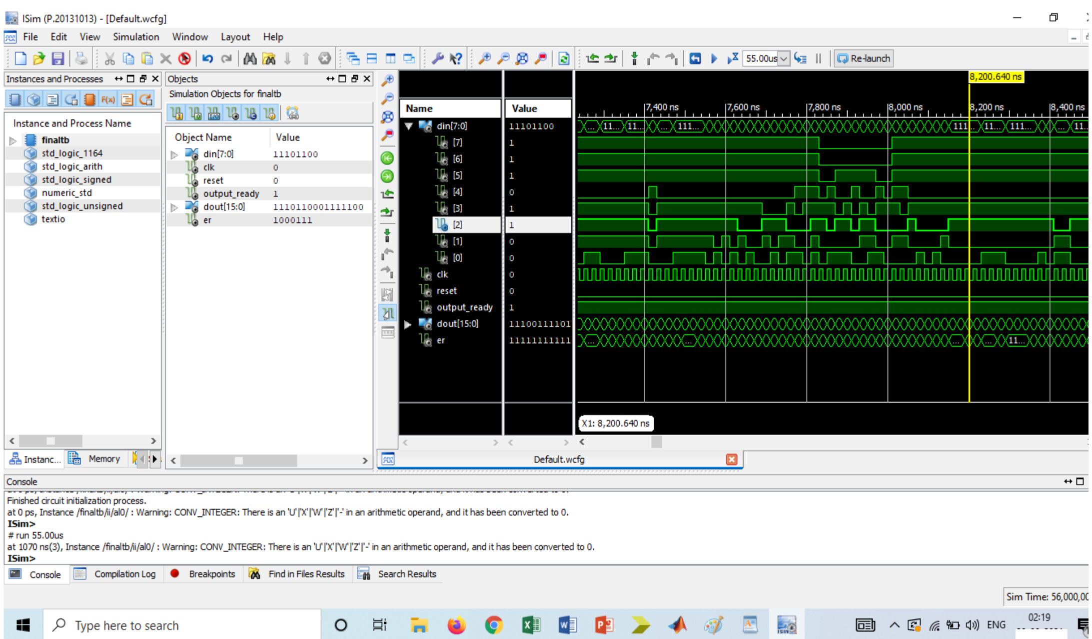

Fig:5.1. Proposed simulation output in XILINX

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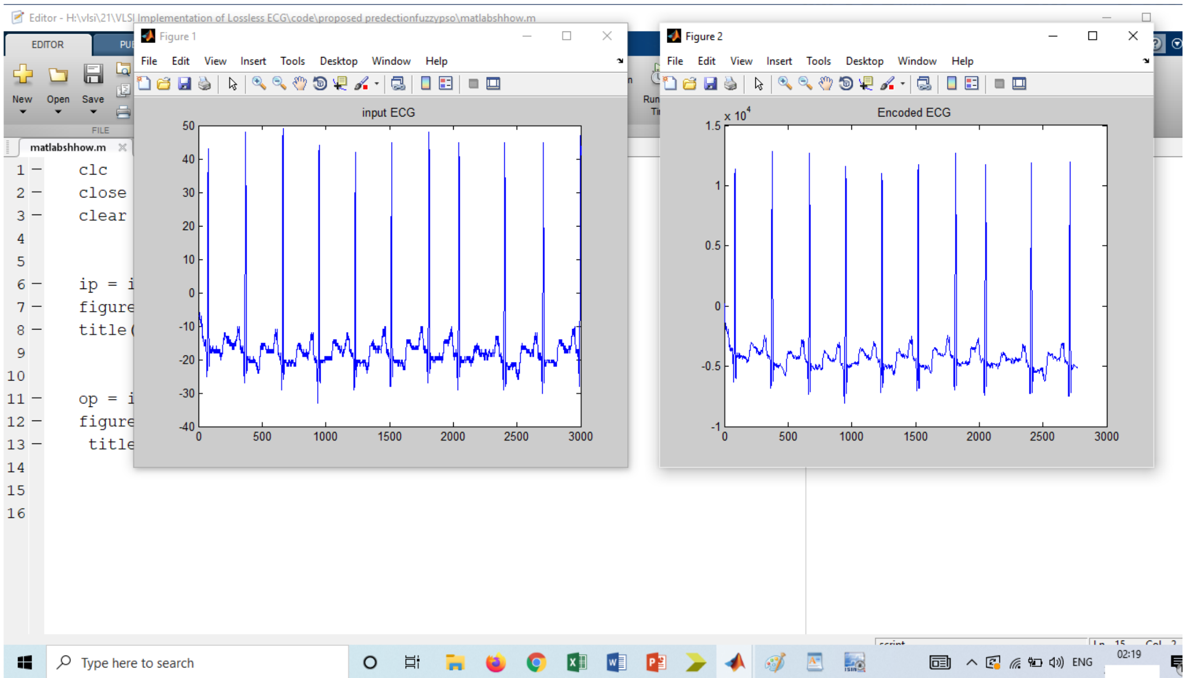

Fig:5.2. Proposed Graphical output in MATLAB

ADVANTAGES:

advantages including minimum signal distortion and low cost. This filter has advantage that this can describe better transformation because this adopts pole and zero both. coefficient compaction, dilution of noise, removal of redundancy Mother Wavelet Filter, lead maximization of coefficient values, best characterization of frequency content Wavelet Thresholding, small wavelet coefficient to zero, retaining or shrinking the coefficients corresponding to desired signal.

APPLICATIONS:

Human Body Communication–Based Wearable Technology for Vital Signal Sensing

Natural and Synthetic Sensors

Toward secure and privacy-preserving WIBSN-based health monitoring applications

Cardiovascular Techniques and Technology

Internet of things, smart sensors, and pervasive systems: Enabling connected and pervasive healthcare

6. CONCLUSION:

This paper presents a low power VLSI implementation of the lossless ECG compression algorithm. The proposed implementation has been tested for different ECG arrhythmia which achieves. The method provides specific advantages due to its applicability to non-stationary and non-linear time series. Perhaps the most difficult problem yet to solve is Also biomedical time series often are recorded over long time spans extending over days and even weeks.

FUTURE SCOPE:

This section discusses the scope for further research related to the automated human physiology and emotion detection techniques. The first part of this research investigated the clinical relevance and discriminating ability of fourth-order spectra in the context of cardiac state categorization. A new clinically significant and reduced dimension hybrid feature set of ECG signals has been presented for an accurate and efficient classification of cardiac states using neural network classifier. The developed algorithm is tested and performance has been evaluated using ECG records loaded from the MIT-BIH Arrhythmia database of Physiobank ATM. This research can be extended to test the developed cardiac state classification scheme on real time ECG signals of human subjects instead of standard database signals. The detailed classification accuracy analysis can be performed by configuring different set of classifiers including support vector machines, extreme learning machines and artificial neural network classifiers. Different set of training algorithms can also be utilized instead of Levenberg Marquardt training algorithm implemented in this research.

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