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ECG ENCODING USING LOW DESNSITY BASED EFFICIENT FUZZY PSO AND GOLOMB-RICE

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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.

Keywords: *Golomb Rice code, electrocardiogram, Fuzzy Logic, Partical Swarm Optimization.*

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 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

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.

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.

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.

EXISTING METHOD:

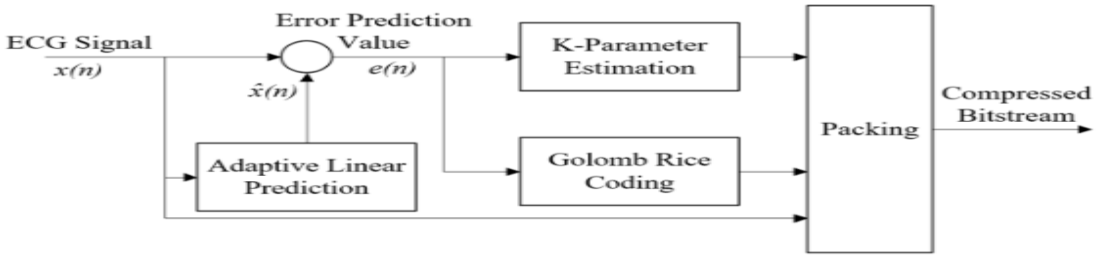

Fig1. Block diagram of the lossless ECG compression algorithm

Generally, ECG data compression has two main processing parts i.e. error prediction and data coding as shown in Figure. The prediction error value, e(n), can be calculated as (1) $e(n) = x(n) - \hat{x}(n)$ (1) where $\hat{x}(n)$ is the prediction value, and x(n) is the value of current sample data in ECG data at time n. This prediction error value is utilized in Golomb code.

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;

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

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

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

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

Taking the characteristics of the ECG signal into consideration, the simple differential predictors with coefficients are used. Due to low complexity computation and good performance in estimating prediction value, the following three differential predictors have been selected in algorithm development as shown in below

$\hat{x} (n) = x (n-1)$

$\hat{x} (n) = 2x (n-1) - x (n-2)$

$\hat{x} (n) = 3x (n-1) - 3x (n-2) + x (n-3)$

PROPOSED TECHNIQUE:

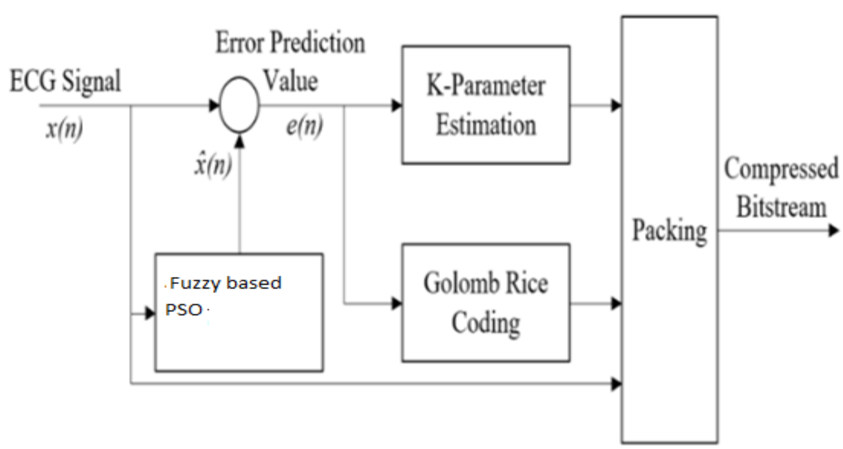

Fig2: proposed technique

FUZZY-BASED PSO PREDICTION METHOD

To improve the accuracy of the prediction technique, particle swarm optimisation (PSO) and fuzzy decision techniques were combined into a novel prediction methodology. The principle of the PSO [7] is used for current particles to figure out the optimised solution for future location. The purpose of the PSO is to search a random particle by a defined mathematical formula, which is suitable for one-dimensional signal prediction. Four main strategies in the proposed PSO prediction lgorithm, in which the prediction of the current value x(t) can be obtained by three passed values x(t −1), x(t −2) and x(t −3). The value of Diff1 is the difference in value between x(t −1) and x(t −2), and Diif2 is the difference in value between x(t −2) and x(t −3). Diff1 and Diff2 can be determined to have a positive or a negative direction of slopes according to the signs of Diff1 and Diff2. The absolution values of Diff1 and Diff2 can be classified into tremendous, large, medium, and small regions according to the correlations with thresholds. Next, a vector V(t) will be the product of an acceleration constant α and a random number β. The PSO uses the results of the fuzzy decision to find the optimal solutions for prediction. The optimal predicted value x′(t) can be estimated approximately by a summation of x(t −1) and V (t). An optimised error rate (e′) can be calculated by the difference between the current value x(t) and the predicted value x′(t). Finally, the optimised error rate (e′) will be sent to the next stage as the predicted difference values for further coding.

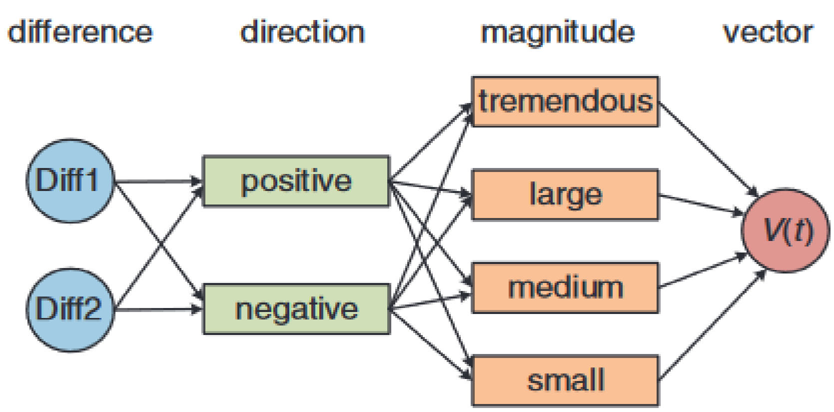

Fig3: Fuzzy based PSO

equations

$$\text{Diff1} = x(t-1) - x(t-2)$$

$$\text{Diff2} = x(t-2) - x(t-3)$$

$$V(t) = \alpha \bullet \beta$$

$$x'(t) = x(t-1) + V(t)$$

$$e' = [x'(t) - x(t)]$$

This consists of one adder, two subtractors, five registers, and one PSO controller. The value of Diff1 is the difference between the values of x(t −1) and x(t −2), which is the same as Diff2 between x(t −2) and x(t −3). Hence, a hardware sharing technique was used. Compared with the previous design [6], this Letter is successful in replacing a subtractor between x(t −2) and x(t −3) by using a shifter register. In addition, the registers in this design are not only used to store the values of related values but also designed as pipeline registers to improve the performance.

LOSSLESS DATA COMPRESSION TECHNIQUE Entropy coding is the part of coding technique in data compression, in which frequently occurring patterns or values are presented with few binary bits and rarely occurring ones are presented with many binary bits. Built on the work of [9], the reference software implementation uses a low-complexity entropy encoder i.e. Golomb–Rice code [8]. C. Content-Adaptive Golomb-Rice code Golomb coding is a data compression scheme based upon entropy encoding and is optimal for alphabets with a geometric distribution. The Golomb-Rice code comprises two parts: quotient and remainder, which are represented by

$$\begin{cases} quotient : \left\lfloor \dfrac{M[n]}{2^k} \right\rfloor ; & encode\ with\ unary\ code \\ remainder : M[n] \bmod 2^k ; & encode\ with\ binary\ code \end{cases}$$

where k represents the number of bits for the remainder, and M[n] is a positive integer. M[n] is achieved by transformation of a prediction error, which may be a negative value, into a positive number. This function can be described by

$$M[n] = \begin{cases} 2e, & e \geq 0 \\ 2|e| - 1, & e < 0 \end{cases}$$

where e is the prediction error value. In algorithm development, a window is used to calculate the distribution of prediction errors [8]. The distribution of prediction error of each window is applied to determinate the k parameter. The size of the window is determined using the QRS segment in the ECG signal. To Golomb-code a number, find the quotient and remainder of division by the divisor. Write the quotient in unary notation, then the remainder in truncated binary notation. In practice, you need a stop bit after the quotient: if the quotient is written as a sequence of zeroes, the stop bit is a one (or vice versa - and people do seem to prefer to write their unary numbers with ones, which is Wrong). The length of the remainder can be determined from the divisor. Golomb-Rice code is a Golomb code where the divisor is a power of two, enabling an efficient implementation using shifts and masks rather than division and modulo. For example, here's the Golomb-Rice code with divisor 4, for numbers up to 15:

Table1: Golomb-Rice encoding table

Value	Quotient	Remainder	Code
0	0	0	1 00
1	0	1	1 01
2	0	2	1 10
3	0	3	1 11
4	1	0	0 1 00
5	1	1	0 1 01
6	1	2	0 1 10
7	1	3	0 1 11
8	2	0	00 1 00
9	2	1	00 1 01
10	2	2	00 1 10
11	2	3	00 1 11
12	3	0	000 1 00
13	3	1	000 1 01
14	3	2	000 1 10
15	3	3	000 1 11

RESULTS:

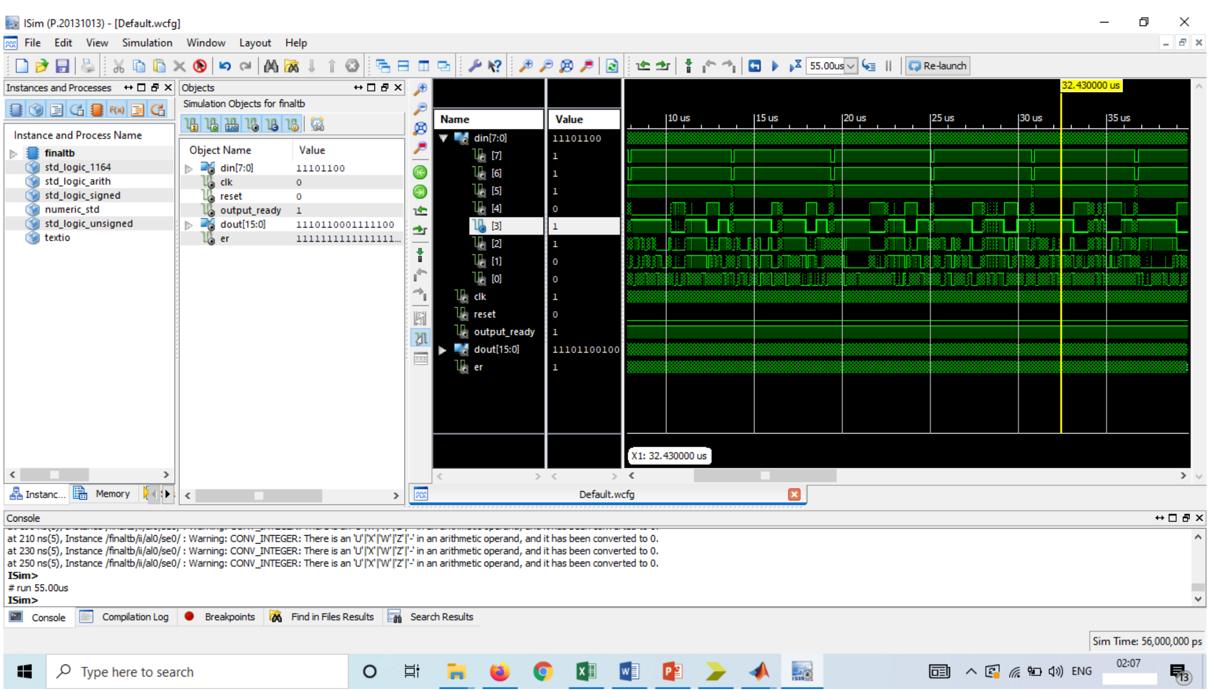

Fig4: Existing simulation output in XILINX ISE14.7

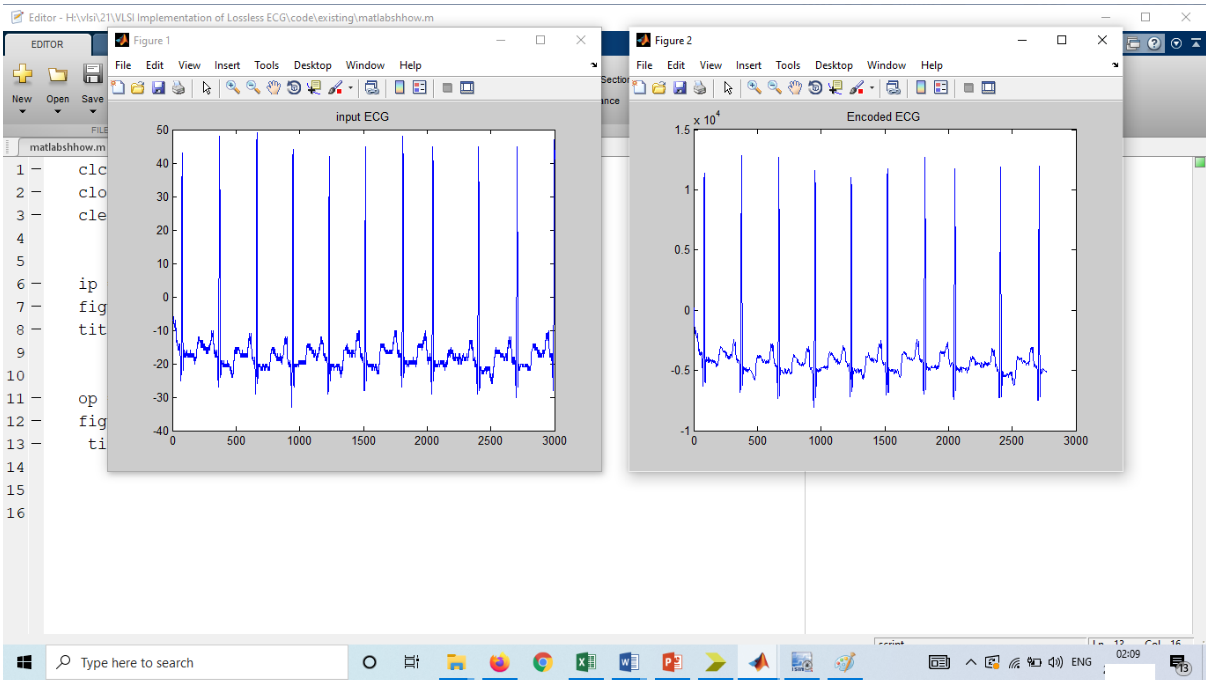

Fig5: Existing Graphical output in MATLAB

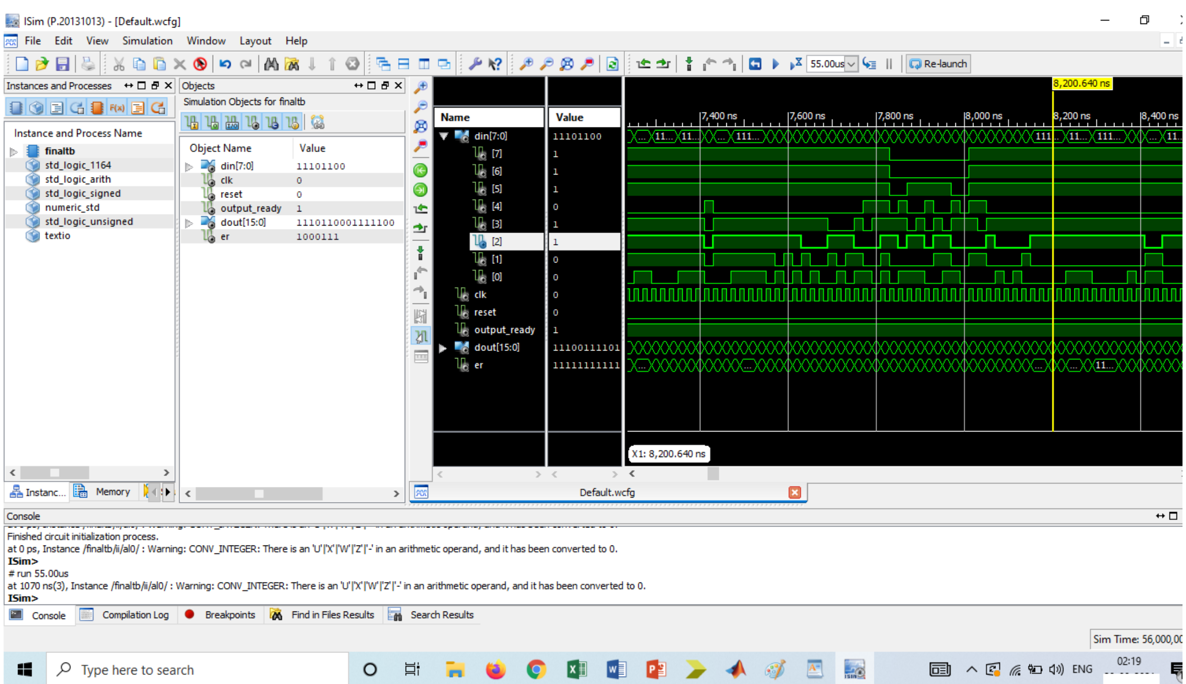

Fig6: Proposed simulation output in XILINX ISE14.7

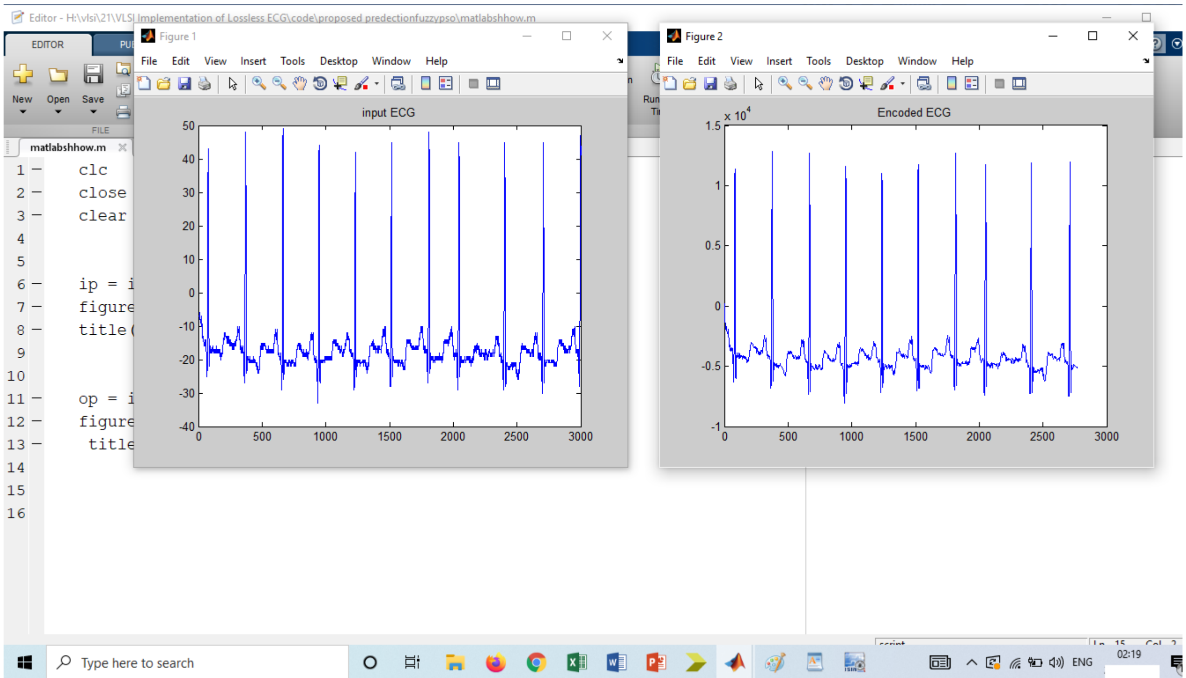

Fig7: Proposed Graphical output in MATLAB

CONCLUSION AND FUTURE SCOPE

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. 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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