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A VLSI BASED HYBRID ECG COMPRESSION SCHEME FOR WEARABLE SENSOR NODE

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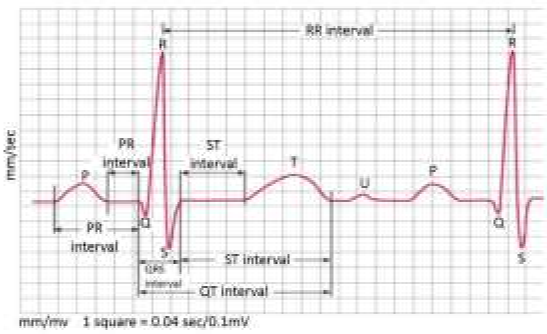
ABSTRACT: ECG (electrocardiogram) is a test that measures the electrical activity of the heart. An efficient and low power VLSI implementation of compression algorithm has been presented in this concept. a hybrid lossless compression algorithm based on Run-length coding and Golomb Rice coding is proposed to enhance the bit compressing rate. 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. Predictive coding is lossless compression technique which allows a compact representation of data by encoding 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 three samples.

KEYWORDS: electrocardiogram, Run-length coding, Golomb Rice coding, Recursive Least Mean Square.

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. 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.



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.

PROPOSED METHOD:

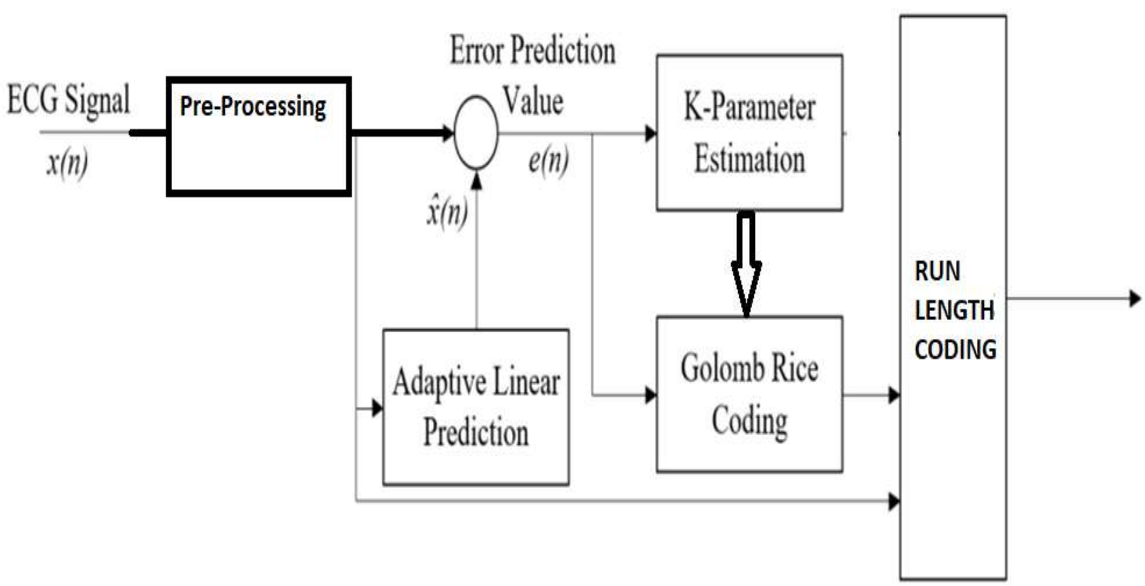


Fig: Proposed method

Generally, ECG data compression has two main processing parts i.e. error prediction and data coding as shown in Fig. The prediction error value, e(n), can be calculated as (1) e(n) = x(n) – x̂(n) (1) where x̂(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 and runlength coding.

ADAPTIVE Linear PREDICTOR: Predictive coding is lossless compression technique which allows a compact representation of data by encoding 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 samples x(n-1),x(n-2),x(n-3),,,,. The sample x(n) is substituted by the prediction difference, PD = x(n)-x'(n). The biomedical signals are fairly slow and these are predictable distribution in nature. Hence we can use the prediction methodology to improve the performance of the encoding algorithm. To improve the performance of prediction, a second order prediction method based on slope prediction along with the first order prediction methodology based on linear prediction which was used to forecast the present value of the biomedical signals by passing two values [1]. As shown in the Figure 1[a], the present value x (n) can be obtained by passing two values of x(n-1) and x(n-2) with the relationship diff-1 is equal to diff-2. [a] diff-1=diff-2 [b] diff-1=2*(diff-2)-(diff-3)

This consists of five registers, one adder, four substractors, one shifter, and one multiplexer. Four of the five registers are used to store the input values of x(n), x(n − 1), x(n − 2), and x(n − 3), and the other one is used to store the value of prediction difference. The register PD(n) is also a pipeline register for improving the performance of the proposed encoder design. The values of diff_2 and diff_3 can be obtained by two substractors. The value of 2*diff_2- diff _3 can be calculated by a shifter and a substractor with the obtained values of diff_2 and diff_3. The predicted value of diff_1 can be selected adaptively from the values of diff_2 and 2*diff_2-diff _3 according to the trend of the signal. Finally, the value of the prediction difference can be produced for entropy coding.

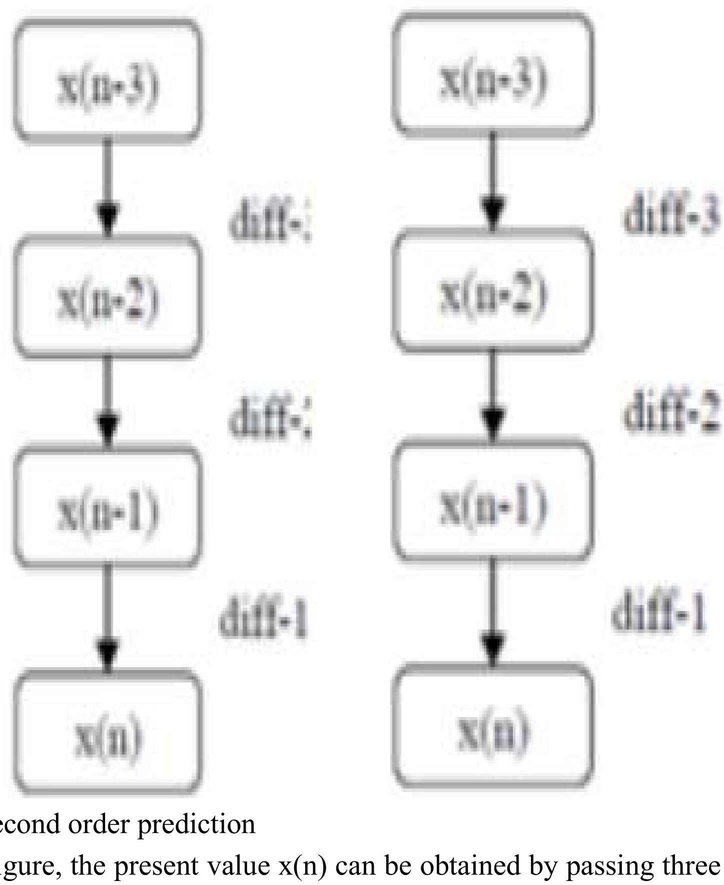
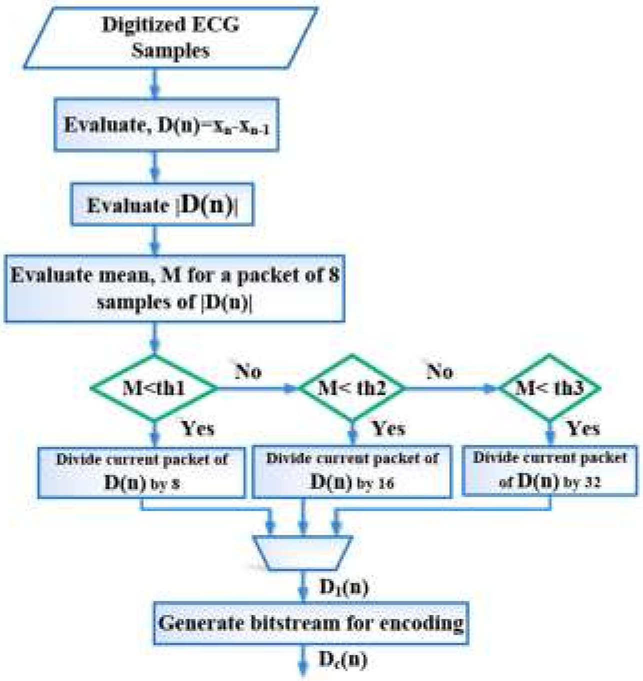


Figure : First order and second order prediction

As shown in the above Figure, the present value x(n) can be obtained by passing three successive samples x(n-1), x(n-2) and x(n-3) with the relationship diff-1 is equal to two times of diff-2 minus diff-3. From this adaptive trending prediction methodology, it is possible to improve the accuracy of prediction. Here, the prediction strategy will be adaptively selected from either first order or second order based on the trend in the signals. The compression and decompression scheme consists of predictor, substractor and entropy encoder and is shown in main Figure.



It scales down the amplitude range compared with that of the digitized ECG samples. A packet size of 8 is chosen from the evaluated first derivative samples. The choice of packet size is based on identifying different regions of ECG, such as the high-amplitude QRS region, through evaluating its mean value. The mean of selected sample size can also incorporate abrupt change in amplitude due to noise. In order to reduce the amplitude further, division operation is performed by selecting proper divisor. The selection of the appropriate divisor is made by taking the mean of each packet from the first derivative absolute value |D(n)|. The mean M of the ith packet is calculated as follows

$$M = \frac{1}{8} \times \sum_{j=i}^{i+7} |D(n)|_j.$$

The calculated mean of each packet is then compared with the three predefined threshold values, which are calculated considering possible maximum of the |D(n)| samples corresponding to three different regions, i.e., low-amplitude region, medium-amplitude region, and high-amplitude region where th3 > th2 > th1. Based on the range of M, three different divisors are selected as shown in Fig. The generated bitstream D1(n) is then sent to the encoder that produces compressed bitstream Dc (n).

B. 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].

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

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

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

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

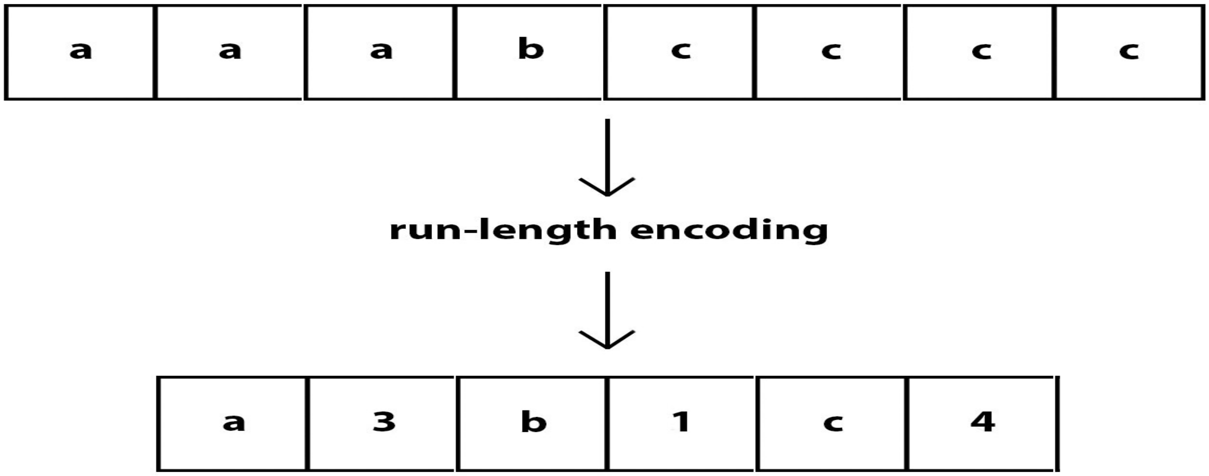
where e is the prediction error value. In algorithm development, a window is used to calculate the distribution of prediction errors [8]. The distribution of prediction error of each window is applied to determinate the k parameter. The size of the window is determined using the QRS segment in the ECG signal. For ALP module, 11-bit input is being processed at every clock cycle. For the first four inputs, linear prediction is performed differently as compared to other inputs as discussed in the proposed original algorithm [8]. This leads to the designing of two different linear predictors. A control unit is controlling the input data by generating control signals for the selection of linear prediction unit as well as sending data from linear prediction units to error predictor. For error predictor, simple arithmetic is present to check whether the number is positive or negative. In error predictor, input data is coming from linear prediction module. The sign bit, which is added in ALP processing, is being evaluated to check whether the number is positive or negative. B. Golomb Rice Coding Golomb rice coding is the most complex and computation intense part in the whole compression algorithm. And due to continuous data processing, the hardware design is designed to keep minimum delay for data processing in Golomb Rice coding. Moreover, area saving techniques were implemented so that the chip area does not get big. Input data is post-processed data of the error predictor module. Data is processed for one complete window so there is a 40x13-bits register to save one window's values. When new window's values are arriving then previous window's values are processed to find the value of U and V, where U and V represent quotient and remainder respectively. So, in general, this module's architecture can be divided into two parts; data controlling part and computation part as shown. In the computation part, operations have been divided into different clock cycles to reduce the processing delay. Instead of using the built-in operators of division or power, bit shifting has been used to perform the multiplication, power, mod and division operations. By using this bit tweaking, the design is able to benefit from the reduction of a number of gates and power consumption. For example, division and multiplication of a number by two have been performed by shifting the value to right and left by 1 bit respectively. Moreover, division is performed after the summation of the values of one window, the range of values will be between 1 to 127. So, the log values of these values have been stored in a log table, which is accessed whenever a log operation is required in the design. A single counter is being used to control data reading and saving to reduce resources usage. Moreover, sharing of the single counter for both controllers leads to less activity as compared to using two counters which results in saving switching power.

RUN-LENGTH ENCODING:

Run-length encoding (RLE) is a lossless compression method where sequences that display redundant data are stored as a single data value representing the repeated block and how many times it appears in the image. Later, during decompression, the image can be reconstructed exactly from this information. This type of compression works best with simple images and animations that have a lot of redundant pixels. It's useful for black and white images in particular. For complex images and animations, if there aren't many redundant sections, RLE can make the file size bigger rather than smaller. Thus it's important to understand the content and whether this algorithm will help or hinder.

History of run-length encoding

This technique was first patented by Hitachi in 1983. It's less popular today because there are other more advanced options available, but you will still find it in use for color for fax machines, icons, line drawings and simple animations. You'll also find it in TIFF and PDF files. However, this compression was regularly used when transmitting analog television signals all the way back to 1967! (Way before Hitachi patented it!) LZ77 is an algorithm that compresses data in a similar way to RLE. It replaces repeated occurences of data with a reference to a single copy of that data that exists earlier in the uncompressed stream. If there's a match to a chunk of data, then LZ77 encodes a match that represents the distance between the two chunks of data and the length of each chunk. To find matches, LZ77 has to track a chunk of recent data, which can be of varying sizes. The bigger the chunk of recent data, the bigger a chunk it can search through for a match. Because it's viewing a chunk of data that can be of varying sizes to find matches, it's sometimes called sliding-window compression. Pairs can repeat multiple times, so it's like RLE, but a bit more complex.



STEPS:

1. Pick the first character from the source string.
2. Append the picked character to the destination string.
3. Count the number of subsequent occurrences of the picked character and append the count to the destination string.
4. Pick the next character and repeat steps 2, 3 and 4 if the end of the string is NOT reached.

RESULTS:

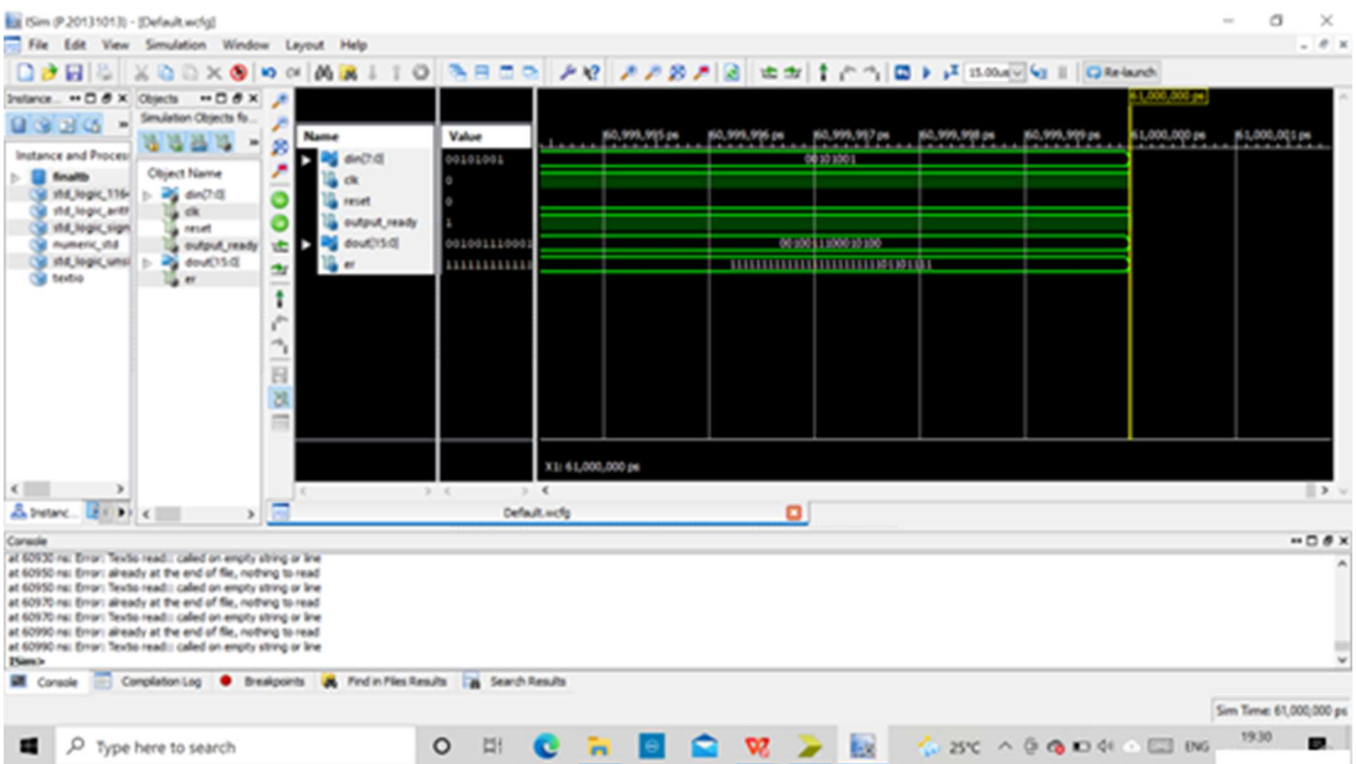


Fig: Proposed simulation result in VIVADO

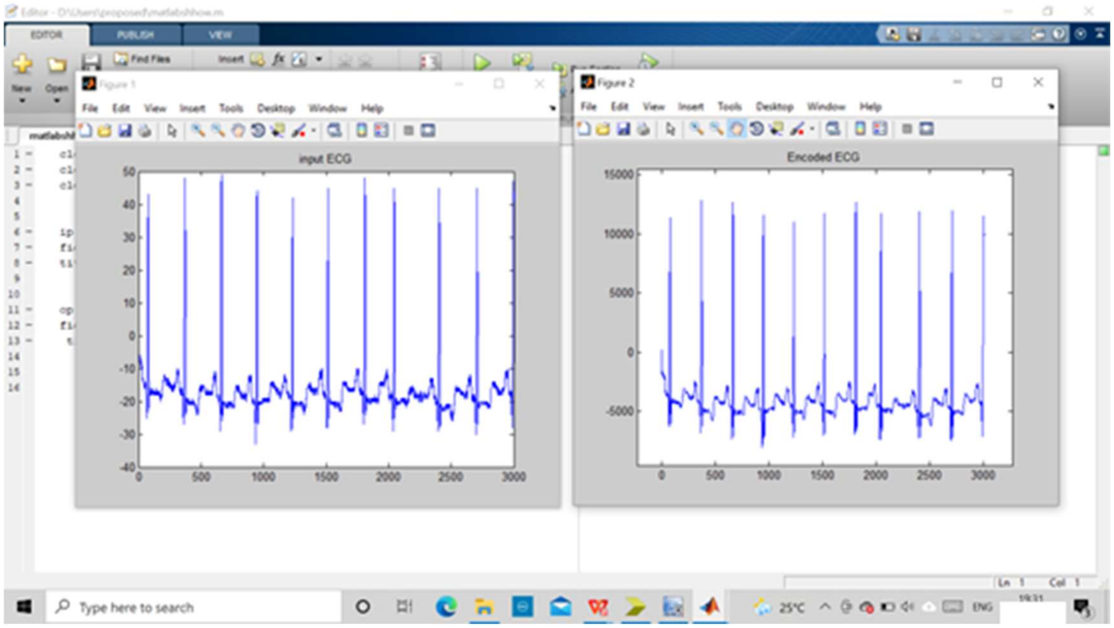


Fig: Proposed Compressed visual ECG in MATLAB

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

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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