Ultra-Low Power ECG Hybrid Compression Architecture with R Peak detection for IoT Healthcare Devices

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Abstract—*Data compression is done in sensors used in ECG healthcare devices for faster wireless transmission. The paper presents an ultra-low power R peak detector and an ECG dictionary based hybrid compression architecture for internet of things (IoT) healthcare devices. Data compression is done in sensors used in ECG IoT health care devices for faster wireless transmission. Ultra-low power electrocardiogram (ECG) processing hybrid architecture with an ample level of accuracy is a necessity in Internet of Things (IoT) medical wearable devices. An absolute-value curve length transform (A-CLT) is proposed that effectively intensify the QRS complex detection with minimized hardware resources. QRS detection is accomplished by using adaptive thresholds in the A-CLT transformed ECG signal. The proposed architecture requires adders, shifters and comparators only. No multipliers required. A lossless compression technique is included into the proposed architecture that use the ECG signal first derivative, variable length encoder and dictionary based code compressor. Dictionary code compression is done using bitmask algorithm. Compression architecture help IoT medical devices to achieve ultra-low power operation (in mW ranges) and minimize the data needed to be transmitted to minimize power consumption for devices equipped with wireless transmitters. The proposed architecture is synthesized using standard-cell-based flow. This technique is used in ECG based IoT healthcare devices such as implantable cardio-converter defibrillator, pacemaker, biventricular pacemaker etc*

Key words:—Electrocardiogram, R peak, absolute value curve length transform, variable length encoder, dictionary code compression, code word length constrained bitmask code compression.

1. INTRODUCTION

ULTRA low power medical devices are essential in the epoch of internet of things (IoT). They achieve ultra-low power operation (mw ranges) and compress the data to be transmitted to minimize power consumption for devices equipped with wireless transmitters. Healthcare sensors apprehend active physiological data for monitoring and diagnosing patients. IoT transfers data to cloud-connected servers. Data compression is done in sensors used in ECG IoT health care devices for faster wireless transmission. ECG is utilized in cardiac arrhythmia prediction. Detect by accurately extracting ECG intervals, amplitudes and wave morphologies of the different ECG signal components such as the P, QRS, and T waves [1].

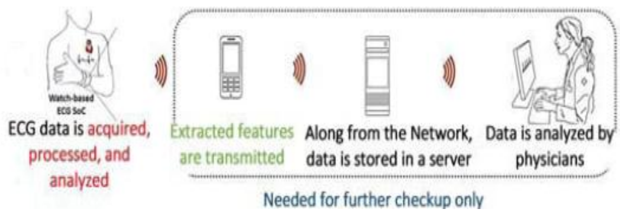


Fig -1: ECG analyzing mechanism

The QRS complex is a principal component of the cardiac cycle. They are used as a reference and represent the depolarization of ventricles in the heart. The time required for the ventricles to depolarize defines the QRS width or interval. One of the efficacious ways of reducing energy consumed in wireless transmitters is to reduce the data transmitted through data compressors. Another option for lessening transmitted or processed data is to decrease the number of samples. Generally microcontrollers could be the central processing unit of an IoT device. IoT healthcare platforms enables minimum local processing and transfers data to cloud connected servers that help resolve drawbacks of holter monitors and similar devices. Various platforms of IoT architectures for healthcare were proposed as in [2]. IoT healthcare connects patients, doctors, and devices according to the ideology as shown in Figure 1 and 2. IoT infrastructure extends from sensors, communication devices up to central servers which assimilate efficient devices.

IoT platform challenges extend from system engineering that elaborate signal acquisition, local processing, transmission, central processing and generating feedback. Each of these stages has its own challenges particularly with the increasing number of connected devices. However, existing micro- controllers have an active power dissipation of greater than 100mW and a leakage power of greater than 1mW which is much higher power dissipation than custom ASIC solutions. The main objective of this project is to present an ECG processing and compression architecture that can help IoT medical devices to attain ultra-low power operation. Compress the data needed to be transmitted to minimize power consumption for devices equipped with wireless transmitters.

Fig -2: IoT healthcare platform

The time required for the ventricles to depolarize specify the QRS width or interval where it typically lasts between 80ms to 120ms[3]. Option for compressing transmitted or processed data is to decrease the number of samples. In [4], a non-uniform time sampling technique is proposed with adaptive sampling rate to lower the energy consumption of the sampling process. Such scheme is applicable for slowly varying signals. In [5] compressed sensing is presented as a probable technique for reducing the sample count that has an advantage in reducing the overall power dissipation. The processed ECG data or extracted feature in the IoT platform is transmitted wirelessly. Wireless data transmission is the most energy-hungry part in IoT devices. One of the effective ways of reducing energy consumed in wireless transmitters is to minimize the data transmitted through data compressors.

2. SUMMARY OF EXISTING SYSTEM

2.1 System Architecture

QRS detection is a challenging task due to the backing reasons. ECG being low amplitude in nature is contaminated by noise and artifacts such as electrode noise, motion artifacts, muscle noise, power-line interference, ADC quantization noise and noise in acquisition devices. Moreover, QRS waves have wide morphological variation among various people with different health conditions. Fig. 3 shows the existing system architecture.

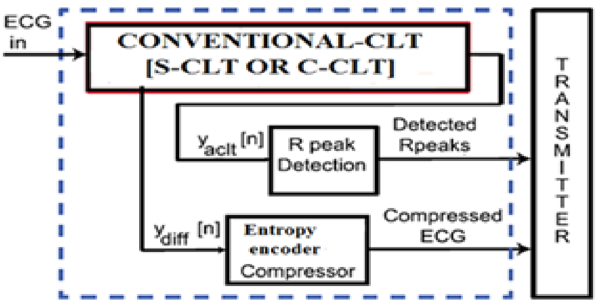


Fig -3: Existing system architecture

2.2 Summary of QRS Detection Architecture

2.2.1 Discrete Wavelet Transform: Wavelet Transform is presented as a tool to analyze ECG signals. QRS detection based on Quadratic Spline Wavelet Transform is reported[6]. Even though the system achieve high sensitivity for QRS detection when validated using MIT-BIH database, its implementation is complex that requires scale-3 wavelet transform and maximum modulus recognition. Its operating power consumption is 0.85μ W.

2.2.2 Differentiation and Threshold: Time domain threshold along with filtering (first derivative, second derivative, both derivatives, matched filter, etc.) are some of the earliest techniques and are suitable for real-time implementation. It was one of the most widely researched and an implemented technique as it was robust in detecting QRS. In [7] QRS detection architecture QRS detection is done using differentiation, moving average and squaring. In [8] Pan and Tompkins algorithm (PAT) was proposed which was one of the most widely researched and implemented techniques as it is robust in detecting QRS [9], [10]. Dynamically adaptive threshold are applied to a squared ECG signal in order to detect QRS peaks. However these approaches still use hardware intensive operations such as multiplication and division.

2.3. Summary of ECG Compression Architectures

2.3.1 Lossless Compressor Based on Linear Slope Predictor: It includes a fixed length packaging scheme for a serial transmission. The architecture was implemented in 0.35µm technology and achieves a compression ratio of 1.25 × at a power consumption of 535nW from a supply of 2.4V for ECG signals that are sampled at 512 Hz. The number of data reduction after encoding is very less in this lossless compressor compared to proposed system.

2.3.2 Lossless-Entropy Encoder with Adaptive Predictor: This system [11] presents in a unique lossless ECG encoder based on adaptive predictor and two-stage entropy encoder. But it achieved a compression ratio of 1.34. In the proposed system the number of samples after encoding is less and encoding is faster.

2.4 Ultra-Low Power Design Techniques

Operating at a low frequency reduces the supply voltage and has advantage in reducing the total power consumption.

$P_{Total} = P_{dyn} + P_{leak}$ (1)

$P_{dyn} \propto C \times f \times V^2$ (2)

$P_{leak} \propto I_{leakage} \times V$ (3)

In duty-cycled ultra-lower power systems, the average power consumption is given. In such duty-cycled systems there is a trade-off between ON-time, leakage power and active power.

$P_{ave} = P_{always\text{-}on} + P_{sleep} + (E_{active} \div T_{wkup})$ (4)

Lowest energy operating point could be obtained depending on the design complexity and power dissipation of each part. Transmission could be done periodically.

3. THE PROPOSED SYSTEM

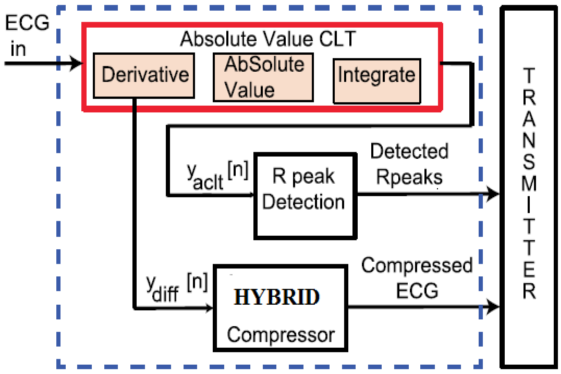


Fig -4: Proposed system architecture

3.1 System Architecture

The proposed QRS detectors robust enough to deal with the noise and artefacts compared to existing method is shown in fig. 4. Filtering has been widely used especially for removing low-frequency noise, baseline drift, and high-frequency interference. Transformation is applied to enhance a portion of the ECG waves. In this proposed technique the pre-processing or filtering and transformation are lumped into one component forming a modified version of curve length transform (CLT). Hybrid compressor consists of an encoder along with dictionary format by which the power and area are reduced[12].

3.2 Algorithm Formulation of R Peak

Fig. 5 is Absolute Value Curve Length Transform (A-CLT) which determines the length of successive points of an ECG signal henceforth provides a way to characterize the high slopes and points that have significant deviation from the baseline. The QRS is characterized by the signal component with the highest slope and amplitude above all other ECG wave components. The A-CLT utilizes this unique behavior of the QRS complex to boost the QRS complex and suppress other ECG wave components. By choosing a proper value for C, a particular portion of the signal is improved and boosted compared to the rest of the signal. The proposed A-CLT performs transformation followed by peak detection using adaptive threshold.

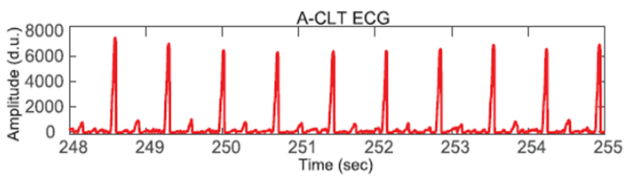


Fig -5: A-CLT Graph

3.3 A-CLT Architecture

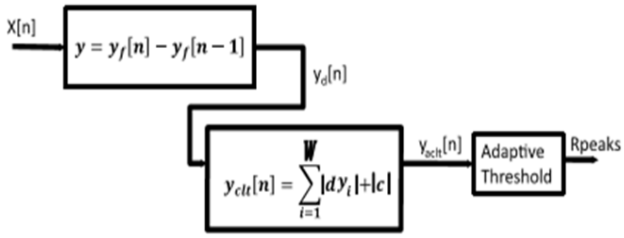


Fig -6: Proposed Absolute Value CLT

Figure 6 shows the proposed A-CLT architecture for detecting the QRS complex. It performs transformation followed by QRS peak detection using adaptive threshold. The transformation is done using derivative, absolute value and integration all lumped into one realization of the A-CLT. The transformation distinctively enhances QRS complex even for noisy ECG signals that is corrupted with baseline wander. Its unique inherent behaviour removes the need for additional complicated circuits for high pass or low pass filters. All the computations for the transformation are performed using addition and shifting. Moreover, comparison is required for detecting QRS-peaks using thresholds. There is no need for multiplication, division or square root. Hence its hardware implementation requires only adders, shifters and comparators. These components are less hardware intensive relative to multipliers, dividers and square-root functions. The integration over a window in the proposed architecture is pipelined. Pipelining enables us to transform directly whenever there is a new ECG sample. Accordingly, the required clock frequency for the architecture is equal to the sampling frequency of the incoming ECG signal. The sampling frequency of the system is set to 250 Hz. This is the lowest operating frequency possible for such configuration. Such a low operating frequency reduces the dynamic power dissipation and the overall system power.

3.4 The QRS Peak Detection

In the proposed system QRS detection is performed using adaptive threshold. The threshold is updated whenever a new beat it detected and is proportional to the mean of the previously detected QRS peaksis repoted in [13]. The QRS detector is robust enough to deal with the noise and artifacts mentioned in the previous section. Filtering has been widely used especially for removing low-frequency noise, baseline drift, and high-frequency interference. Our proposed system provides optimized QRS detection architecture that could deal with all the artifacts with minimum hardware resources without compromising the accuracy. An optimum threshold factor is obtained using the standard database from physionet. The experiment is done on MIT-BIH.

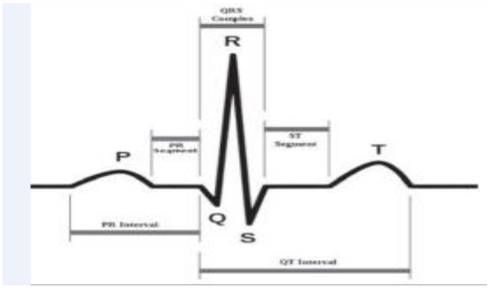


Fig -7: Schematic Representation of an ECG Wave

The threshold is evaluated based on the equation given as:

$Th_i = Th_{factor} \times \text{mean} \sum_{k=i-8}^{i} R\text{peaks}_k$ (5)

Figure 7 shows the schematic representation of an ECG wave. Here the ECG wave consists of few intervals. They are PR interval, PR segment, QT interval, ST segment and QRS complex. Variation in width of each wave is due to variation in different parts of heart.

3.5 Optimization Parameters

According to the proposed architecture, there are two parameters that need optimum selection. These are the window size and threshold factor. Note that for a fixed window the threshold factor has a major impact on wave.

3.6 ECG Hybrid Compression Architecture

The term hybrid means combination of variable length encoder and dictionary based code compression technique. Proposed hybrid compression architecture is shown in Fig. 8. The system takes the first derivative and split the sequence in group of eight bits then does an entropy (variable bit length) compression. Then output from encoder is combined together and forms a large sequence. This sequence is again grouped in eight bits to generate dictionary code. Here undergo CLCBCC with MBSDS. Then dictionary code compressed data is loaded into load register and output is serially fed to the transmitter. The 1st derivative requires only adders. The entropy encoder requires comparators or priority encoder and dictionary code compression which could make it easily implemented.

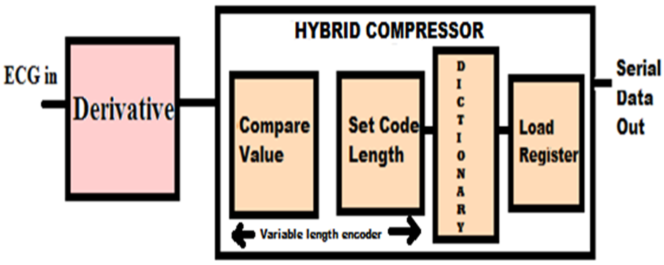


Fig -8: Proposed Hybrid Compression Architecture

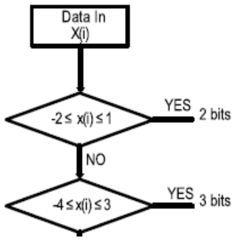


Fig -9: Variable Length Encoder Flowchart

Table -I: Encoder Output

BITLINE NUMBER	INPUT DATA X(i)	ENCODED OUTPUT
0	00000000	00
1	00000001	01
-1	00000010	10
-2	11111111	11
2	00000010	010
3	00000011	011
-3	11111101	101
-4	11111100	100

3.7 Variable Length Encoder

The variable length encoder consists of two blocks. They are compare value followed by set code length. The derived ECG signal is fed to the encoder block. Less number of bits is used for low amplitude signals and more number of bits is used for large amplitude signals. Such encoding reduces the code word length required to represent the whole ECG signal. Therefore reduces the power consumption of medical health care devices while wireless transmission. The variable length encoder flowchart is given in fig. 9.

The inserted data should lie within the intervals given in the flowchart. On data insertion, if the data lies between the interval -3<x(i)<2 then its code word length is last two bits of original inserted data. Otherwise, that is if it doesn't lie in the 1st interval the data is jumped to the next interval -5<x(i)<4 and its code word length is last three bits of original data. The comparator code is detailed in table I.

By this process the 16000 bits of ECG signal is compressed to 9999 bits. There is a reduction of 5999 bits by this encoder technique. Further reduction is accomplished by the dictionary based code compression.

3.8 Dictionary based code compression Algorithm

Dictionary based code compression Algorithm used along with variable length encoder reduces time consuming and can decrease area usage. Dictionary code compression is done using bitmask algorithm is reported in [14]. Depending on the type of transmission technique, an identifier could be added to mark the beginning and end of the decoded variable length data bits. A small separated dictionary and variable mask numbers are used with the Bit

Mask algorithm to reduce the code word length of high frequency instructions. Variable mask numbers are used to eliminate the encoding redundancy.

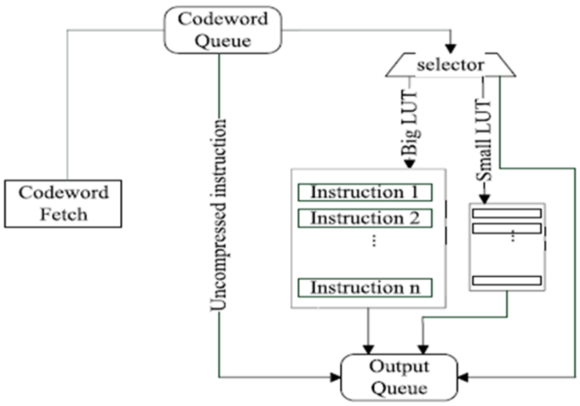


Fig -10: Specific Architecture for CLCBCC

The combination of these methods is called as the code word length constrained bitmask code compression (CLCBCC). Compressing the high-frequency instructions with the same code word length as other low-frequency instructions will result in inefficient compression. To overcome this problem, these high-frequency instructions are separated into another small dictionary to obtain shorter code word lengths. Two luts are used for the bit mask approach as shown in fig. 10. A large lut is used to compress low frequency instructions, and a small LUT is used to compress the extremely high-frequency instructions. The specific dictionary architecture for the CLCBCC is shown in Fig. 10.

The encoding format is shown in Fig. 11, which contains four situations, such as uncompressed, matched with small dictionary, matched with large dictionary, and matched using a variable number of masks.

Dictionary based code compression algorithm is given as: inputs - 8-bit instruction symbols, small dictionary size, big dictionary size, mask types.

OUTPUT: Compressed code words

BEGIN

STEP 1: Calculate the frequency distribution of all instruction symbols

STEP 2: Select the highest unique frequency symbols into the small dictionary based on the step 1. STEP 3: For every unique instruction symbols which are not selected into the small dictionary, use the big dictionary or LUT.

STEP 4: Use the bitmask based method to compress all instructions based on current dictionaries and mask setting.

STEP5: Return the compressed code words.

END

Figure 12 shows an example of selection using mixed bit saving dictionary selection. All symbols in this example are 8 bit wide, the dictionary contained 256 entries, only one 2-bit mask was used, and the overhead of the identification tag is 2-bit. After each symbol transformation to the nodes, each node contained its frequency value. If the vector is bit masked then its masking position, mask value and index value is stored.

Table -2: Identification Tag

BIT TYPE	IDENTIFICATION TAG
Uncompressed bit	00
Compressed with small LUT	01
Compressed with big LUT	10
Use bit mask	11

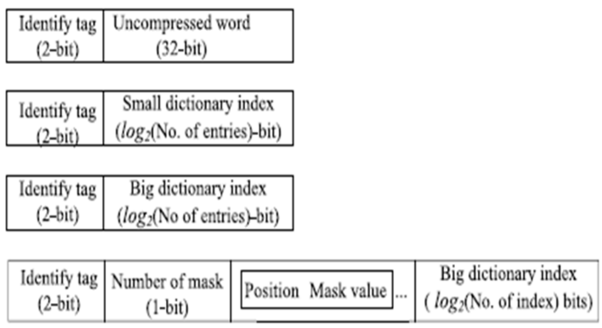


Fig -11: Dictionary Encoding Format

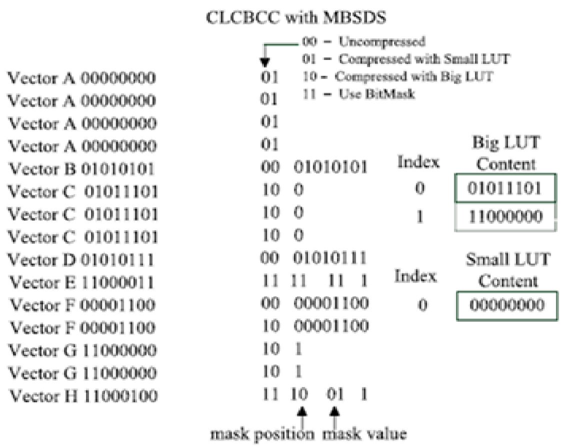


Fig -12: CLCBCC with Dictionary Format

If the vector is uncompressed, the sequence as it is stored. And the vectors mostly occurring or high frequency is stored in small LUT indexed as 0. Also the vectors with low frequency is stored in big LUTs indexed as 0 and 1.Table II shows the indentification tag provided for each bit. .On dictionary code compression the 9999 bits get compressed to 6459 bits. By the encoder and dictionary compressor a drastic variation is attained in area, power and delay compared to previous system.

4. PERFORMANCE AND RESULTS

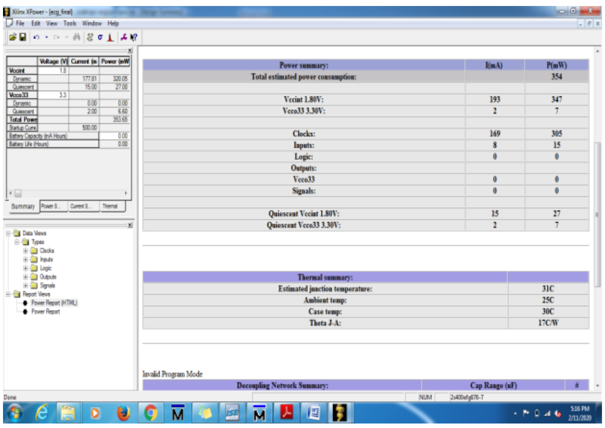
To evaluate the performance of the algorithms, manually annotated ECG signals from physionet MIT-BIH Arrhythmia

Database and QT database are used [15]. The MIT-BIH database contains randomly selected subjects as well as subjects with known arrhythmia that have clinical significance.

Table -3: Compressor Comparison with Existing Work

	EXISTING SYSTEM	PROPOSED SYSTEM
Area	15,095	6,270
Power	720mW	354mW
delay	15.193nsec	13.074nsec

Moreover, the subjects are both men and women aged between 22 - 89 years. It has been widely used as a standard database for evaluating ECG QRS detectors. Table III shows the comparison of the proposed compressor with existing work. The proposed lossless compression architecture consumed only 354mW when operating at frequency of 75.485MHz. The proposed system consists of a dictionary compressor followed by the entropy encoder. However the compressor is part of a complete ECG processing system. Since the compressor subsystem performance such as power, delay and area are used for comparison. Fig 13, 14 and 15 shows the output of area, delay and power of the proposed system. Fig 16 and 17 shows the output waveform which is the ECG analog and digital waveform from which the R peak is detected.



5. CONCLUSION

This project presents a novel real-time QRS detector and ECG hybrid compression architecture for energy constrained IoT healthcare wearable devices. A novel absolute-value curve length transform (A-CLT) enhances the QRS complex detection with minimized hardware resources. The proposed architecture implementation requires only adders, shifters, and comparators and avoided the need for any multipliers. The QRS detection is accomplished using adaptive thresholds in the A-CLT transformed ECG signal. Furthermore, a lossless compression technique was incorporated into the

Fig -13: Power consumption

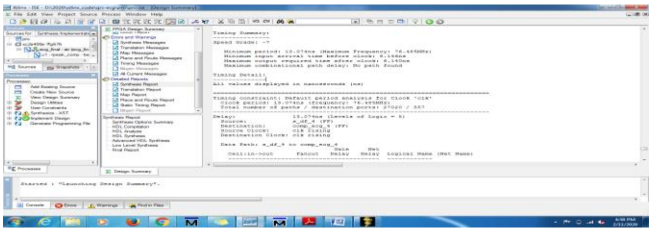


Fig -14: Delay

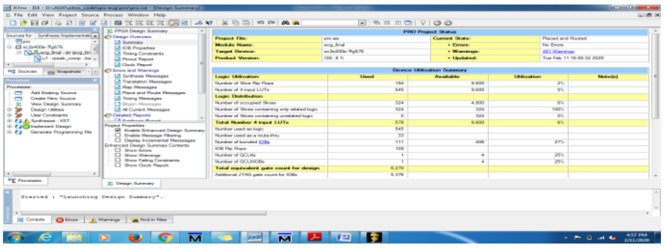


Fig -15: Area

Fig -16: Output ECG analog waveform

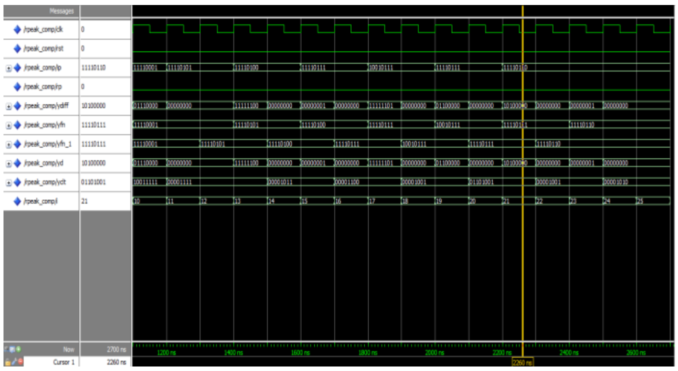


Fig -17: Output ECG digital waveform proposed architecture that uses the ECG signal first derivative and dictionary based variable length encoder.

Compression architecture help IoT medical devices to achieve ultra-low power operation (in µW or nW ranges) and minimize the data needed to be transmitted to minimize power consumption for devices equipped with wireless transmitters. The proposed architecture was synthesized using standard-cell-based flow. This technique is used in ECG based IoT healthcare devices such as implantable cardio-converter defibrillator, pacemaker, biventricular pacemaker etc. Expected average compression ratio of 2.05 when evaluated using MIT-BIH database. Proposed QRS detection architecture was implemented using 65nm low-power process.

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