



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJIRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 12, Issue 4, April 2023

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

 9940 572 462

 6381 907 438

 ijirset@gmail.com

 www.ijirset.com

Hybrid ECG Compression Using VLSI

Boopathy S, Nandhini B, Shivani T U, Vibisha J

Department of Electronics and Communication Engineering, Kumaraguru College of Technology, Coimbatore, India

Department of Electronics and Communication Engineering, Kumaraguru College of Technology, Coimbatore, India

Department of Electronics and Communication Engineering, Kumaraguru College of Technology, Coimbatore, India

Department of Electronics and Communication Engineering, Kumaraguru College of Technology, Coimbatore, India

ABSTRACT: Wearable sensor nodes produce and send a large amount of data during intelligent long-term monitoring of any biomedical signal in wireless body area networks, increasing transmission power consumption. This letter presents a lossless data compression method for an electrocardiogram signal monitoring device to decrease data storage and power usage. In order to increase the bit-compressing rate, a hybrid lossless compression algorithm based on Run-length coding and Golomb-Rice coding is suggested. The MIT-BIH arrhythmia database is used to perform the lossless encoding scheme, which results in a compression ratio of 2.91. The data compression algorithm is applied in a VLSI-based architecture in 90nm CMOS technology, requiring 18.78 W of power at 100 MHz operating frequency and 1.2 V supply voltage, and taking up space.

KEYWORDS- Sensor node, wireless body area network, lossless compression, and battery management (WBAN).

I. INTRODUCTION

Wearable sensor nodes generate a lot of data because they have capabilities for continuous monitoring. Additionally, since data transmission consumes about 72% of the sensor node's power, it is difficult for these nodes to maintain extended battery life. Through the use of lossy compression methods, high compression ratios (CR) can be attained at the expense of reconstruction error. In and, several lossy encoding techniques are used, where to obtain high CR, computationally challenging algorithms extract features from a particular region of the signal. Prediction-based methods with Golomb-Rice encoding are used in lossless compression. Predicted difference is stored with variable-length encoding using an adaptive linear predictor.[1] It is described how to implement adaptive Golomb-Rice entropy coding in a VLSI-based adaptive linear predictor. Compressed sensing uses a power-gating strategy to create a low-power FPGA-based compression design. These methods utilize computationally demanding operations, which have an impact on the area overhead and power consumption of the wearable node. The VLSI-based lossless compression schemes with optimum area overhead and power usage are in high demand for real-time, online implementation on the wearable sensor node for biomedical signal monitoring. However, it requires further research to discover a better approach for improvement in CR, and as with the increase in transmitted data load in sensor node, the lifetime of the battery degrades significantly.

II. LITERATURE REVIEW

Implementing a lossless ECG compression algorithm on VLSI for low power devices. This article proposes a lossless ECG Compression Algorithm for electrocardiogram (ECG) data encoding to reduce transmission time and save storage space. Memory-less architecture has been used to take advantage of compression algorithm's ability to save storage space and cut down on transmission time. This succinct demonstrates a high clock speed VLSI implementation of an effective lossless compression algorithm. A content-adaptive Golomb Rice code and an adaptive linear prediction method make up the ECG compression algorithm. The application of a compression algorithm on a VLSI chip has been shown to be effective and low power. The suggested VLSI design replaces the various arithmetic operations with bit shifting operations to increase performance. The MIT-BIH arrhythmia library has undergone VLSI implementation, which results in a lossless bit compression rate of 2.77. Additionally, the VLSI

architecture has 3.1 K gates and the chip's core uses 27.2 nW of electricity while operating at 1 KHz. The 90 nm CMOS process has a 0.05 mm² core size.[2]

Multi-Channel ECG Lossless Compression System Implemented in VLSI. The electrical action of the heart is captured using an electrocardiogram (ECG). Long-term signal tracking will generate a lot of data from the instrument. Consequently, a successful lossless ECG compression method can aid in reducing storage space. The hardware architecture of a multi-channel lossless ECG compression device is presented in this succinct. The algorithm used by the device includes both adaptive and multi-channel linear prediction. Additionally, entropy coding employs the Golomb rice code (GRC). The hardware solution was created to utilize the least amount of hardware complexity possible. Additionally, the architecture can handle multiple channels simultaneously to achieve a high throughput. For reasons of testing and verification, the PTB database has been used. TSMC 180nm was used to execute this design.

A 2.63 W ECG Processor for Implantable Cardiac Monitoring Device with Adaptive Arrhythmia Detection and Data Compression. We present a long-term implantable cardiac monitoring (ICM) system for arrhythmia diagnosis that uses an ultra-low power ECG processor ASIC (application specific integrated circuit) with R-wave detection and data compression. To identify arrhythmia with sporadic abnormal heartbeats, a low computation overhead adaptive derivative-based detection algorithm for potential arrhythmia recording is suggested. A hierarchical data buffer structure is suggested that stores three different kinds of data in order to save as much cardiac information as possible with the limited memory size available in the ICM device, including the R-peak values and interval durations of >2000 beat cycles, as well as the raw ECG data segments of 2 seconds and the compressed ECG data segments of 45 seconds[3]. For the ECG data compression, a modified swinging-door-trending (SDT) technique is suggested. In order to achieve low dynamic power consumption and leakage, the ASIC was implemented based on completely customized near-threshold standard cells using thick-gate transistors in 65-nm CMOS technology.

Lossless and Lossy Direct Compression Design for Low-Temperature Wearable Devices with Multi-Signal Symptom Detection. The lossless and lossy direct compression design (LLDC) is suggested for wearable technology in this article. The compression design for cardiovascular conditions can be used in conjunction with the electrocardiogram (ECG), blood pressure (BP), and respiration (RESP). The suggested LLDC has the ability to recognize abnormal symptoms and dynamically switch between various sample intervals and data precisions. In our tests, the wearable devices' transmitted power and temperature are decreased and the symptoms are identified. With percentage root-mean-square differences less than 6.5%, the compression ratios for ECG, BP, and RESP are up to 7.94, 6.06, and 6.51 respectively. The energies of the wearable devices for ECG, BP, and RESP are decreased by 50%-87%, 38%-89%, and 41%-89%, respectively, while the temps are decreased by 2.6°C-4.2°C, 1.3°C-3°C, and 1.7°C-3.6°C.[4]

Making use of related prior information to compress ECG signals. Electrocardiogram (ECG) signals are transmitted in wireless body area networks using data compression methods to conserve power. (WBAN). Among these methods, compressed sensing enables the encoding of sparse or compressible signals with a minimal amount of measurements. Despite not being sparse, ECG signals can be rendered sparse in another domain. There are many sparsifying methods, but when signal clarity and energy usage are crucial, the current methods can be improved.

III. SYSTEM IMPLEMENTATION

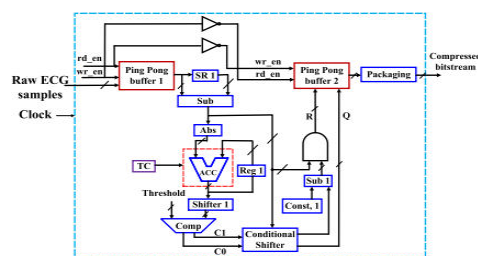


Fig. 1. Block diagram of the hardware architecture

This part talks about the proposed algorithm's hardware implementation. This displays the suggested architecture at the block level. It shows how compressed data is produced from ECG sample data and then packaged. The digitized input data stream comprises of 11 bits/sample. The data are first fetched through a shift register (SR 1), and then the "sub" block subtracts them as stated in (1) to produce the first-order derivative, or $D(n)$. By using the absolute values of the eight samples' means as a starting point, the suitable divisor k is chosen. that the $D(n)$. The "Abs" block uses the 2's complement method to generate the absolute values of $D(n)$. The accumulator "ACC," which is managed by a terminal counter TC, adds the numbers. After adding eight samples to each packet, the result is extracted using TC. The mean value of the current packet is produced by "Shifter 1" right-shifting the matching output. The calculated mean is compared to the "Comp" block using cutoff values that have been predetermined ($th1$, $th2$, and $th3$), resulting in control signals $C0$ and $C1$. The conditional shifter shifts $D(n)$ to the right to obtain the quotient value Q based on the combos of $C0$ and $C1$. In addition, the conditional shifter has a left shift module that, in response to the control impulses $C0$ and $C1$, left shifts the constant value "2" to produce the logic values 8, 16, and 32. There is no left or right shift when the requirement " $C0C1=00$ " is met. To remove constant 1 from the logic value produced by the left shift module, use the subtractor "sub 1". The remainder R is produced by logically adding the $D(n)$ number with the "sub 1" output. The obtained values are packaged before being sent to the distant computer. The suggested architecture is based on first derivative operations to minimize complex operations, and submodules are implemented with subtractors, shifters, counters, and comparators.[5]

A. Electrocardiogram:

The procedure of electrocardiography involves creating an electrocardiogram (ECG or EKG), which is a recording of the electrical activity of the heart. It is a heart electrogram, which uses sensors applied to the skin to create a graph of voltage versus time for the electrical activity of the heart. Each cardiac cycle results in the depolarization and repolarization of the cardiac muscle, which is detected by these sensors. (heartbeat). Numerous cardiac abnormalities, including irregular heartbeat (such as atrial fibrillation and ventricular tachycardia), insufficient coronary artery blood flow (such as myocardial ischemia and myocardial infarction), and electrolyte disturbances, result in changes in the typical ECG pattern. (such as hypokalemia and hyperkalemia). Traditionally, "ECG" has referred to a 12-lead ECG that was recorded while laying down, as explained below. While some models of smart watches can also capture an ECG, other devices, like a Holter monitor, can record the electrical activity of the heart. This allows for the capture of the general magnitude and direction of the electrical depolarization of the heart at every instant during the cardiac cycle. The P wave, which represents depolarization of the atria, the QRS complex, which represents depolarization of the ventricles, and the T wave, which represents repolarization of the ventricles, are the three major elements of an ECG.

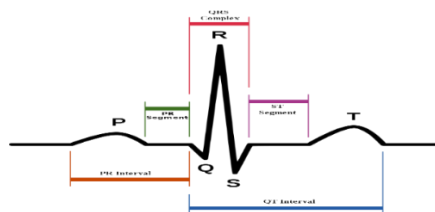


Fig. 2. Electrocardiogram

B. Electrodes and Leads:

The conductive pads that are affixed to the body's surface are called electrodes. The electrical potential difference between the two corresponding sites of attachment can be measured using any pair of electrodes. Such a couple creates an advantage. Wilson's central terminal (WCT), whose potential is described as the average potential measured by three limb electrodes that are attached to the right arm, the left arm, and the left foot, respectively, is a virtual electrode that can also be used to create "leads" between physical electrodes.[6]

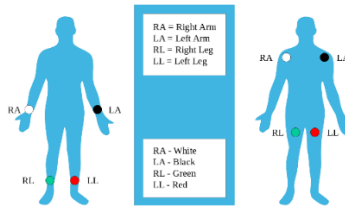


Fig. 3. Proper placement of the limb electrodes

C. IoT healthcare platform:



Fig. 4. IoT healthcare platform

By precisely extracting the ECG intervals, amplitudes, and wave morphologies of the various ECG signal components, such as the P, QRS, and T waves, ECG is used in cardiac arrhythmia prediction and diagnosis. As a point of reference, the elevation of the heart's ventricles is represented by the QRS complex, a crucial part of the cardiac cycle. For typical beats, its amplitude increases to 1 or 2 mV above or below the isoelectric line, and for abnormal beats, it can increase several times. The QRS width or interval, which usually lasts between 80 and 120 milliseconds, is determined by the amount of time needed for the ventricles to depolarize. Since the QRS complex has a higher amplitude than the other ECG wave components, finding the precise position of the QRS complex in ECG signal analysis is essential for automatic ECG delineation methods. In the scale of nW, ultra-low-power ECG analog-front end could be obtained, and 3nW ECG front-end is reported. At 187.5 kbps, the transmitter's output is 4.18 W.

This paper's primary goal is to present an ECG processing and compression architecture that can assist IoT medical devices in achieving ultra-low power operation (in the W or nW ranges) and minimizing the amount of data that needs to be transmitted in order to reduce power consumption for devices equipped with wireless transmitters. A single transformation-based architecture for ECG QRS detection without multipliers is suggested.

Designing electronic biomedical devices with integrated circuit (IC) technology is the subject of extensive study. The cardiac pacemaker, which is frequently used to identify, monitor, and ensure that the patient's heart-beating rate is within a safe range, is one of the most widely used biomedical devices. The ECG detector uses digitalized ECG data from an analog-to-digital converter to assess the heartbeat's rhythm and rate. (ADC). [7]

The P wave, QRS complex (a combination of Q, R, and S waves), and T wave are the three waveforms that make up the ECG signal in general, as shown in. Over the RR interval, the QRS complex typically has more energy and a greater amplitude than the P and T waves. (interval between two adjacent R waves). Accurate QRS complex (or R wave) detection is necessary to accurately track the patients' heart rates. However, accurate QRS complex detection with low computational complexity continues to be a difficult issue due to the various types of noise that can occur over the ECG signal. In particular, a new generation of technology known as body sensor networks (BSNs) has assumed a growing significance in the provision of ongoing diagnosis support and medical care. Wearable electrocardiogram (ECG) sensors are one of the crucial physiological sensor nodes in BSN and are used to measure the frequency and regularity of heartbeats as well as the size and location of the chambers, the presence of any heart damage, and the effects of medications or heart-controlling devices.

It is necessary to filter out or eliminate all of these noise sources in order to perform effective and precise detection. Typically mixed with a dc component of up to mV and a common-mode component of up to 1.5 V resulting from the electrode-skin contact and the potential between the electrodes and ground, respectively, the front

end of an ECG sensor should be able to handle extremely weak signals ranging from 0.5 to 5.0 mV. The useful bandwidth of an ECG signal for general healthcare applications can vary from 0.5 to 50 Hz depending on the particular application. A clinical ECG program typically uses a bandwidth between 0.05 and 100 Hz. While it could go up to 1 kHz for late-potential measurements for a monitoring application in critical care units. (pacemaker detection). The frequency-based ECG filtering algorithms for QRS detection, i.e., a band-pass filter with a center frequency in the region of 10–17 Hz, have received a lot of attention. To determine the location of QRS waves, the signal after crossing the filter may be squared or averaged over a number of samples.[8] In order to reduce the computational complexity for a wearable ECG QRS detector, we use two of the most basic morphological operators (erosion and dilation) in this work. To test the technique, a very-large-scale integration (VLSI) architecture that is both power and size efficient is designed and implemented on an FPGA.

II. WORKING PRINCIPLE 1.METHOD FOR LOSSLESS COMPRESSION:

In the suggested method, the current sample value and the prior sample value are used as the initial evaluations of the first-order derivative $D(n)$. Most of the computed $D(n)$ revolve around zero. It displays the histogram of $D(n)$ values for ten ECG impulses. The $D(n)$ values for various areas vary as a result of this amplitude variation. With and without preprocessing, the suggested algorithm has been tried on digitized input ECG signals. The evaluation of the first derivative $D(n)$ from the provided digitized ECG samples serves as the basis for the compression method. $D(n)$ equals $x[n] - x[n-1]$.

In comparison to the amplitude range of the digitized ECG data, it scales the range down. From among the evaluated first derivative samples, an 8-packet size is selected. The selection of the packet size is dependent on the evaluation of the mean value of the ECG to identify various ECG regions, such as the high-amplitude QRS region. The chosen sample size's mean can also include a sudden shift in amplitude brought on by noise. By choosing the right divisor, the division operation is carried out in order to further decrease the amplitude. By subtracting the mean of each packet from the first derivative absolute value $|D(n)|$, the proper divisor is chosen. The following formula is used to determine the i th packet's mean M : M is equal to the total of $|D(n)|$ from $[i+7$ to $j=i]$. [9]

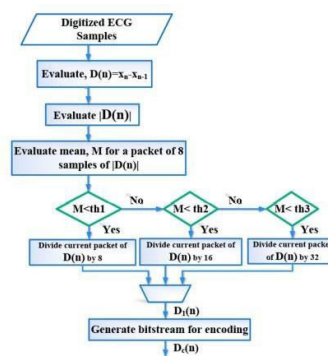


Fig.5. Flowchart of proposed lossless compression scheme

The three predetermined threshold numbers are then compared to the calculated mean of each packet. These values are determined by accounting for the potential maximum of the $|D(n)|$ samples that correlate to the low-amplitude, medium-amplitude, and high-amplitude regions, respectively, where $th3 > th2 > th1$. Based on the range of M , three different divisors are selected. The generated bitstream $D1(n)$ is sent to the encoder that produces the compressed bitstream $Dc(n)$.

2. RUN LENGTH ENCODING

One of the effective lossless coding methods that has been applied when the input bitstream's amplitude values are considerably lower is golomb-rice coding. In Golomb-Rice coding, the quotient and residual are determined by a divisor parameter of 2's power. The residual and quotient are encoded in binary and unary formats, respectively. A stop bit clearly distinguishes the remnant from the quotient, and the bitlength of the remainder depends on the



divisor. The adaptive region-based divisors, which can be represented as a power of 2, are best suitable for Golomb-Rice coding because the amplitude of the ECG is already suppressed through the calculation of $D(n)$

$$\text{Quotient} = \lfloor D(n) / 2^k \rfloor, \text{ where } k=3, 4, \text{ or } 5. D(n) \bmod 2^k, \text{ where } k = 3, 4, \text{ or } 5.$$

By calculating the mean amplitude of $|D(n)|$, or MR, for three distinct regions—high-amplitude region, medium-amplitude region, and low-amplitude region—the parameter k is chosen. MR is then utilized to determine the best quotient numbers for $D(n)$. Following the requirement that $k = \log_2 MR$, three k values for each area are chosen from MR. The histogram of the ten ECG impulses' MIT-BIH database quotient values. It demonstrates that a sizable portion of quotients have values of zero. For the same collection of signals, a continuous run of zeros is extracted because the majority of occurred quotient values are equal to zero. It shows unequivocally that there are many zero runs above 25. Therefore, run-length coding for zero can enhance CR more than Golomb-Rice coding. Run-length coding is therefore used in a hybrid method for zero quotient values while Golomb-Rice coding is used for nonzero quotient values.[10]

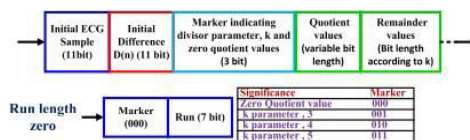


Fig.6. Data packaging in the compression scheme

3. PACKAGING DATA

The ECG data is compressed in real time for a 10-s window size after encoding. Unique identifiers are incorporated into the compressed bitstream during packaging. The original ECG signal's compressed bitstream begins with the first 11 bits of the first ECG sample. The fact that the compressed bitstream $D_c(n)$ is taken from the first-order derivative D helps the decoder reconstruct the encoded signal (n) . The compressed bitstream contains the encoded divisor k in the shape of a marker, which represents various areas of the encoded ECG signal. The hybrid coding method requires the compressed bitstream to have distinctive markers to distinguish between Golomb-Rice coding and run-length zero coding. Any value of the zero quotient in the $D_1(n)$ is preceded with the marker "000" and the number of runs of zeros in the run length. As seen when applying the suggested algorithm on the MIT-BIH arrhythmia dataset, the bit length for runs of zeros is fixed at 7 bit taking a maximum possible run into account. The quotient values in the data stream, whose bit length relies on the run value and k -parameter, are concatenated with the remainder values. The nonzero values are encoded using the Golomb-Rice code, which has a binary coded remainder portion and a unary coded quotient part (logic 1 is used). The Golomb-Rice code's unary coded quotient values are uniquely identified by markers that all begin with the number "0." The decoder must check and match for the markers at the end of each bitstream that represent remainders because the number of bits for the remainder is set according to the marker.

Group	Run-length	Group prefix	Tail	Codeword
A1	0	0	00	000
	1		01	001
	2		10	010
	3		11	011
A2	4	10	00	1000
	5		01	1001
	6		10	1010
	7		11	1011
A3	8	110	00	11000
	9		01	11001
	10		10	11010
	11		11	11011

Fig 7. Golomb coding example with parameter $m = 4$

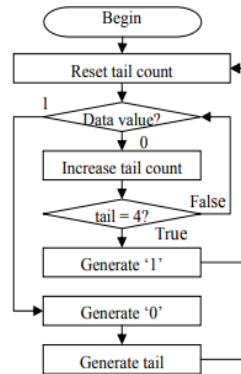


Fig 8. Golomb encoder algorithm (parameter m = 4)

The flow chart in Figure 8 can be used to explain the Golomb encoder paradigm. The quantity of "0"s in the incoming data determines the tail count. When reading "0s," the tail count will rise proportionally until it hits the "m" parameter, at which point a "1" will be produced as the output data. The method will produce a '0' that serves as a separator between the prefix and the tail if the input data is a '1', and it will output the current tail count as the encoded string's tail. The algorithm then watches for the next input of data before restarting the tail count.[11]

4. DICTIONARY-BASED APPROACH

Code compression methods that use dictionaries offer both efficient compression and quick recovery. The fundamental concept is to use a dictionary to exploit frequently happening instruction sequences. The recurring occurrences are swapped out for a code term that directs the reader to the dictionary's index where the pattern is found. Both code words and uncompressed instructions are included in the compressed software. A basic program binary is used to demonstrate dictionary-based code compression in Fig. 3.8. The binary comprises of ten 8-b patterns, i.e., a total of 80 b. There are two 8-b lines in the dictionary. The dictionary needs 16 b, and the compressed application needs 62 b. The CR in this instance is 97.5%. This instance of a variable-length encoding is provided.

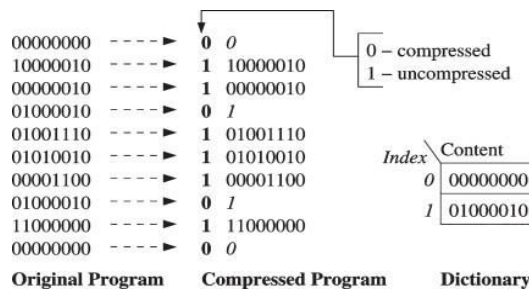


Fig 9. Dictionary Method

Enhanced Dictionary-Based Method By taking mismatches into account, two recently suggested techniques enhance the traditional dictionary-based compression method. Finding instruction sequences that vary by a small number of bits (Hamming distance) and storing that information in the compressed program and updating the dictionary is the basic concept. (if necessary). The number of bit shifts taken into account during compression will determine the CRs. It goes without saying that more matching patterns will be produced if more bit changes are permitted. The compressed program's size will, however, grow in proportion to the number of bit locations.[12]

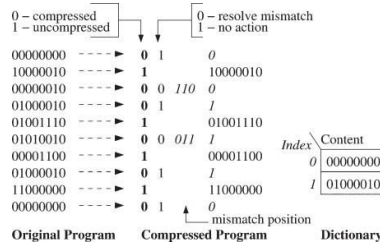


Fig. 10. Improved dictionary-based code compression.

illustrates the enhanced dictionary-based strategy. This scenario only takes 1-b change into account. To specify whether mismatches are taken into account or not, an additional entry is required. Another field is required to specify the bit position that differs from an item in the dictionary in the event that a mismatch is taken into account. For instance, the first dictionary entry (index 0) on the sixth bit position and the third pattern (from the top) in the original program are distinct. (from left). In this case, the CR is 95%.

III. RESULTS AND DISCUSSION

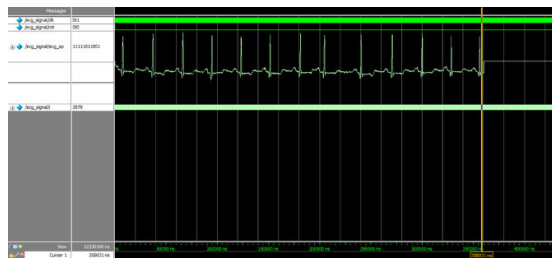


Fig.11. Simulation result of input ecg signal

In comparison to the amplitude range of the digitized ECG data, it scales the range down. From among the evaluated first derivative samples, an 8-packet size is selected. By choosing the right divisor, the division operation is carried out in order to further decrease the amplitude. By subtracting the mean of each packet from the first derivative absolute value $|D(n)|$, the proper divisor is chosen



Fig.12. Simulation result of existing method

In Golomb-Rice coding, the quotient and residual are determined by a divisor parameter of 2's power. The residual and quotient are encoded in binary and unary formats, respectively. A stop bit clearly distinguishes the remnant from the quotient, and the bitlength of the remainder depends on the divisor. The adaptive region-based divisors, which can be represented as a power of 2, are best suitable for Golomb-Rice coding because the amplitude of the ECG is already suppressed through the calculation of $D(n)$.

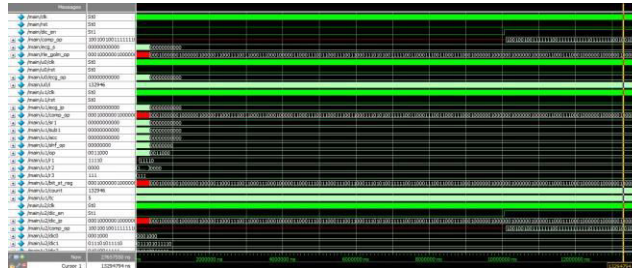


Fig.13. Simulation result of proposed method

A hybrid lossless ECG compression architecture based on sensor nodes is demonstrated in the proposed study to improve CR. The proposed compression technique has a high CR and performs well in the sensing node. Effective compression is also made possible by a multi-level approach based on the choice of dictionaries, golomb, and runlengths.

IV.CONCLUSION

In the proposed study, a sensor node-based hybrid lossless ECG compression architecture is shown to increase CR. The suggested compression method works well in the sensing node and has a high CR. Additionally, a multi-level compression strategy based on the selection of dictionaries, golomb, and runlengths aids in achieving effective compression. Low power is used by the suggested design at an operating frequency of 100 MHz. The suggested architecture is compatible in miniaturized sensor nodes due to nominal power usage and area overhead with a maximum operating frequency of 250 MHz. Additionally, for a 1- minute transmission time, this transmission mode saved 6% of the transmission power compared to uncompressed ECG. The suggested system can be expanded to accommodate additional biomedical data.

REFERENCES

- [1] F. Nasimi, M. R. Khayyambashi, N. Movahhedinia, and Y. W. Law, "Exploiting similar prior knowledge for compressing ECG signals," *Biomed. Sig. Proc. Control*, vol. 60, 2020, Art. no. 101960.
- [2] R. F. Yazicioglu, S. Kim, T. Torfs, H. Kim, and C. Van Hoof, "A 30 μ w analog signal processor ASIC for portable biopotential signal monitoring," *IEEE J. Solid- State Circuits*, vol. 46, no. 1, pp. 209–223, Jan. 2011.
- [3] C. J. Deepu, X. Zhang, C. H. Heng, and Y. Lian, "A 3-lead ECG-on-Chip with QRS detection and lossless compression for wireless sensors," *IEEE Trans. Circuits Syst. II: Exp. Briefs*, vol. 63, no. 12, pp. 1151–1155, Dec. 2016.
- [4] S.-L. Chen and J.-G. Wang, "VLSI implementation of low-power cost-efficient lossless ECG encoder design for wireless healthcare monitoring application," *Electron. Lett.*, vol. 49, no. 2, pp. 91–93, 2013.
- [5] S.-Y. Lin, H.-T. Lin, and Y.-Y. Lin, "Lossless and lossy direct compression design with multi-signal symptom detection for low-temperature wearable devices," *IEEE Sensors J.*, vol. 19, no. 2, pp. 715–725, Jan. 2019.
- [6] C.-H. Luo et al., "An ECG acquisition system prototype design with flexible PDMS dry electrodes and variable transform length DCT-IV based compression algorithm," *IEEE Sensors J.*, vol. 16, no. 23, pp. 8244–8254, Dec. 2016.
- [7] Y. Yin et al., "A 2.63 μ w ECG processor with adaptive arrhythmia detection and data compression for implantable cardiac monitoring device," *IEEE Trans. Biomed. Circuits Syst.*, vol. 15, no. 4, pp. 777–790, Aug. 2021.
- [8] J. Ma, T. Zhang, and M. Dong, "A novel ECG data compression method using adaptive fourier decomposition with security guarantee in e-health applications," *IEEE J. Biomed. Health Informat.*, vol. 19, no. 3, pp. 986–994, May 2015.
- [9] T.-H. Tsai, N.-C. Tung, and D.-B. Lin, "VLSI implementation of multi-channel ECG lossless compression system," *IEEE Trans. Circuits Syst. II: Exp. Briefs*, vol. 68, no. 8, pp. 2962–2966, Aug. 2021.
- [10] K. Li, Y. Pan, F. Chen, K.-T. Cheng, and R. Huan, "Real-time lossless ECG compression for low-power



wearable medical devices based on adaptive region prediction,” Electron. Lett., vol. 50, no. 25, pp. 1904– 1906, 2015.

[11] T.-H. Tsai and M. A. Hussain, “VLSI implementation of lossless ECG compression algorithm for low power devices,” IEEE Trans. Circuits Syst. II: Exp. Briefs, vol. 67, no. 12, pp. 3317–3321, Dec. 2020.

[12] N. Attarmoghaddam, S.H.Khayat, and M. Maymandi-Nejad, “FPGA implementation of power and area efficient compressed sensing for multi-channel ECG compression,” in Proc.24th Iranian Conf. Elect. Eng., 2016, pp. 1027–1032.



INNO SPACE
SJIF Scientific Journal Impact Factor
Impact Factor: 8.423



ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

9940 572 462 **6381 907 438** **ijirset@gmail.com**



www.ijirset.com

Scan to save the contact details