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Golomb Rice Coder-Based Hybrid ECG Compression System †

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Abstract: Heart-related ailments have become a significant cause of death around the globe nowadays. Due to lifestyle changes, people of almost all age brackets face these issues. Preventing and treating heart-related issues requires electrocardiogram (ECG) monitoring of the patients. The study of patients' ECG signals helps doctors identify abnormal heart rhythm patterns by which screening problems like arrhythmia (irregular heart rhythm), myocardial infarction (heart attacks), and myocarditis (heart inflammation) are possible. The need for 24-h heart rate monitoring leads to the development of wearable devices, and constant monitoring of ECG data leads to generating a large amount of data since wearable systems are resource-constrained regarding energy, memory, size, and computing capabilities. The optimization of biomedical monitoring systems is required to increase their efficiency. This paper presents an ECG compression system to reduce the amount of data generated, which reduces the energy consumption due to the transceiver, which is a significant part of the overall energy consumed. The proposed system uses hybrid Golomb-Rice coding for data compression, a lossless data compression technique. The data compression is performed on the MIT BIH arrhythmia database; the achieved compression ratio of the compression system is 2.75 and 3.14 for average and maximum values, which, compared to the raw ECG samples, requires less transmission cost in terms of power consumed.

Keywords: ECG compression; power management; data compression; MIT BIH arrhythmia; Golomb-Rice Encoder

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1. Introduction

Advancements in sensory systems, VLSI technology and wireless sensor networks (WSN) have opened up new avenues of technological applications. Wearable technology has emerged as a promising market, a collusion of various technologies catering to multiple applications. With the healthcare landscape increasingly embracing personalized medicine, the global wearable sensor market is projected to experience a robust compound annual growth rate (CAGR) of around 38% between 2017 and 2025. Notably, the development of smartwatches is anticipated to exhibit an exceedingly rapid rate of expansion during this period [1]. Any wearable technology has a standard building block, e.g., sensors, processors and communication units. These technologies rely on a basic unit, i.e., "data". Every wearable technology aims to collect, process and communicate acquired from the sensors [2]. Some primary design constraints every wearable technology aspires to achieve are size, memory management, power management, latency and computational efficiency. Out of these metrics, power management is the most sought-after area in which optimizations are performed, and this is because wearable technologies have a limited size, resulting in fewer batteries [3]. The communication system consumes most of the energy from the various subsystems discussed. The prime reason is the limited computational capacity of these systems; hence, the acquired data needs to be transmitted to a central system, resulting in energy consumption. The extent of transmission is directly proportional to the amount of data being sent, which, for a physiological monitoring system, is very large when constant information about body vitals is needed.

2. Literature Survey

Data compression techniques aim to reduce the extent of generated data to minimize the time and power consumption due to transmission and memory. Various data compression schemes have been devised. Major bifurcation among these techniques is based on data retrieval after compression, which constitutes lossless data compression and lossy data compression methods. The whole compressed data can be retrieved in the lossless methods, but these methods result in lesser compression ratios (CR), which is defined as the ratio of original ECG data to compressed data. On the other hand, complete data retrieval is not possible in the lossy methods, but when compared with lossy methods, these can produce a greater CR. This category's most commonly used schemes are transforming coding, vector quantization, and fractal compression. The selection of data compression methods is application-dependent. Lossy methods are generally used in applications where a specific amount of loss in data doesn't affect the performance of the systems, e.g., audio compression, video compression, gaming, and multimedia streaming. In comparison, lossless methods are used in data-critical applications like databases, scientific data compression, biomedical data, and communication systems. Hybrid methods use predictive and run-length coding to balance CR and Quality [4]. Various hardware implementations for ECG data compression have been developed, aiming at low-power applications. Y. Zou et al. proposed a hardware model for ECG acquisition based on wavelet transform; this implementation uses a high frequency of operation and is a lossy method [5]. As a result of which, this method is not viable for wearable sensor systems. C.J. Deepu et al. used a prediction-based hybrid algorithm for data compression [6]. F. Nasimi et al., Lin Y et al., and Chen Y. et al. implemented ECG hardware using lossless methods producing high CR values, but these methods require a large number of complex computations for data retrieval, which degrades the energy efficiency of the system [7,8]. Tsung-Han Tsai et al. developed a low-power data compression system for multichannel data using predictive and entropy coding [9]. Another similar study by Sarma J. et al. devised a hardware implementation of lossless data compression for wearable nodes; this method uses linear filtering, run-length encoding, and Golomb-rice coding for data compression [10]. Tsai and Kuo implemented a lossless compression scheme that uses linear prediction for prediction accuracy and GRC for entropy coding. This method uses basic digital circuits to implement the subsystems, resulting in power-efficient operation and few logic gates achieving less chip area [11].

3. Methodology

This section discusses the methodology used in the system. Various subsystems are discussed below, and Figure 1 depicts the steps involved in the ECG compression system:

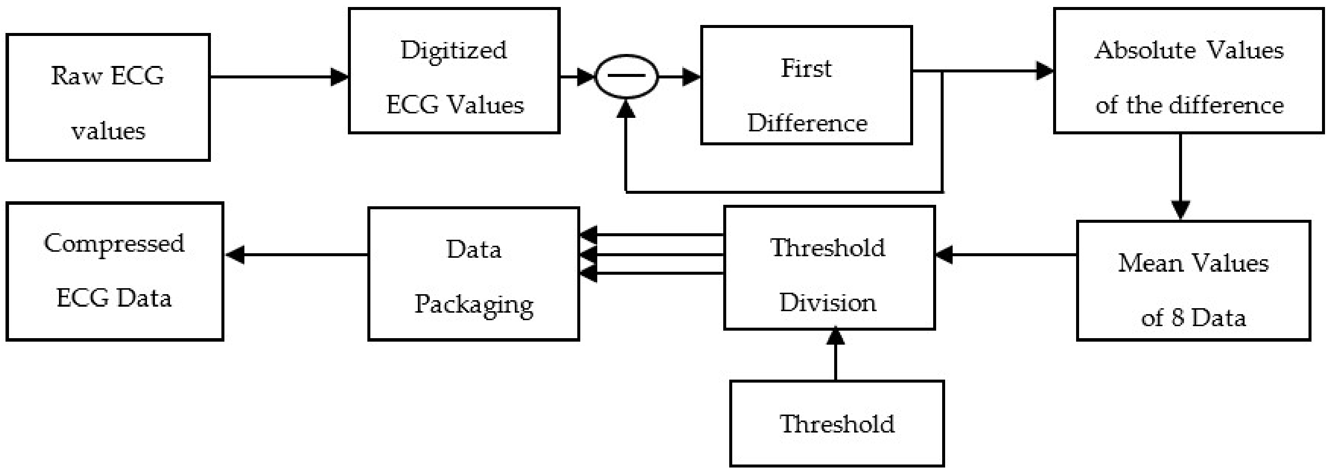

Figure 1. Epileptic Seizure Detection Methodology.

The derivative block is required to obtain the first difference of the ECG values taken from the MIT BIH arrhythmia dataset, and it finds the difference between the present value and the previous sample value. This step fulfils two purposes. Firstly, it reduces the amplitude values of the data samples since the ECG signals have values close to each other. This also minimizes the number of iterations of the compression algorithm since a zero value of difference results in no additional computational cost for the calculation of quotient and remainder. After the derivative block, the magnitude of the first difference values is taken, and a packet of 8 values is chosen to find the respective means. This operation is done to maintain the amplitude values and to provide immunity towards noise levels. To achieve better compression ratios, it is required to have a minimum value of amplitudes possible as it requires the minimum number of bits for representation. The acquired mean values are compared with a threshold value1, which is selected based on the amplitude regions in the ECG values, which are mainly divided into three central regions: low, medium and high amplitude. Obtained mean values are subjected to threshold comparison with chosen threshold values T1, T2, and T3. The output of this comparison determines the factor by which the 8-bit packet will be divided. This packet is the same one that was chosen earlier to find the mean. The division operation further reduces the amplitude values. Further steps involve the encoding of values based on the division.

The Golomb-Rice encoder performs the encoding of the ECG values, and this block is the most essential part of the data compression system. The Golomb-Rice coding (GRC) method is usually employed where the amplitudes are very low in value. First, the samples are divided into groups of symbols, and then these symbols are assigned a code word, which is usually equal to the number of parameters subtracted by the decided coder parameter. This parameter can be decided based on various signal metrics like variance or geometric mean to incorporate the maximum number of reoccurring sample values.

In GRC, the sample values are segregated into two parts upon parameter division, i.e., quotient and remainder. For these obtained quotients and remainders, separated coding schemes are used. Quotients are coded in a unary scheme. GRC is popular due to numerous reasons, such as its low complexity for hardware and software implementations, its viability for various sample data types, and it is a lossless scheme; therefore, it is suitable for applications where sample drops can degrade the efficiency. Here, the value of k is chosen based on the threshold comparison with the obtained mean values. It is observed that the quotient values of samples have a very high frequency over zero values, which can result in a further reduction of the number of bits used for encoding. If the number of consecutive zeroes is obtained for a run of encoding, then a binary number can signify the run length rather than sending that much number of zeros. This method further reduces CR.

$$Quotient = \left[\frac{D(n)}{2^k}\right], \text{ where, k = 3,4,5} \quad (1)$$

$$Remainder = D(n) \bmod 2^k, \text{ where, k = 3,4,5} \quad (2)$$

The obtained quotient values are then coded further to enhance CR run-length encoding (RLE), which is used to encode the consecutive zero quotient values. RLE aims to reduce the redundancy due to the repeated number of characters. RLE is useful in applications where there are repeating sample values in succession to each other. A particular marker bit needs to be used at the decoder end to understand that the RLE code has arrived; in this case, "000" is used as a marker to identify that the runs of zeros have arrived. The data obtained after encoding contains various values, i.e., Raw ECG, Mean, Absolute values, quotients and remainders. The last step remains to combine the essential information for transmission. The packaging is done in two different ways, one for zero values and the other for non-zero values of quotient. The packaging starts with the initial value of the 11-bit ECG signal, which is followed by the initial value of the difference. The next block is the marker indicating the factor used for the division of values specified. This block also indicates the zero quotient values by indicating a distinct marker. After this, quotient values are sent, which are variable in length due to a unary coding scheme. In the end, the remainder is sent over in binary form, hence, shown as a variable in the data frame. For a run of zeros, frame 3,4 is replaced by marker 000, and the variable run length is coded in binary format. The explained packaging format used here is for 8-bit packets, and this process is repeated for all 450 packets of 8 bits, resulting in a total of 3600 values. The overall hardware of the compression system is shown in Figure 2.

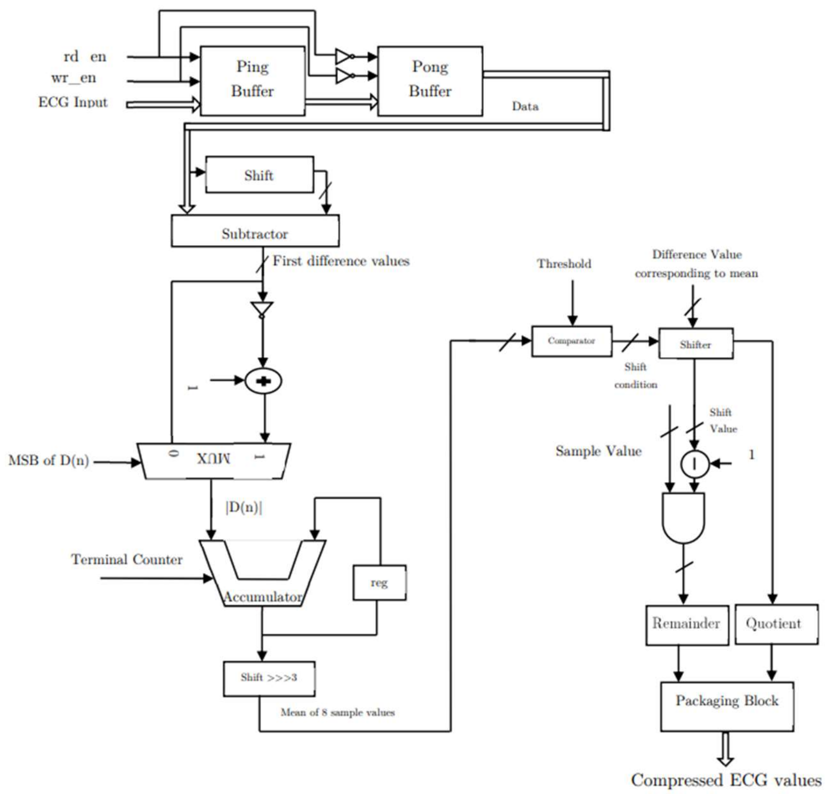

Figure 2. The overall architecture of the compression system.

4. Results

The results obtained from waveforms and RTL schematic from the compression system are shown in this section. At the positive edge of the clock cycle and low reset value, the addresses of the memory locations from where the values are to be taken are loaded. Data out gives the corresponding value of the ECG signal from the buffer. The clock period is 2, and the complete data takes 7.2 microseconds to reach into the system. Figure 3 shows the output of the shift operation and the subtraction to find the value of the first difference. It can be observed that some values are exceptionally large. This is due to 2's complement representation of negative numbers in binary format. In the next step, absolute values are taken for the first difference. After that, 8 sample values are taken to find the sum and shift right by 3 to obtain the mean of the values. The obtained values are then given to the threshold comparator, which decides the factor from which the sample values corresponding to the mean should be divided and quotients and remainders are obtained. Quotient values for respective data samples are taken, and the packaging for 8-Bit samples are done. It is observed that for the first 8 data samples containing 88 bits of data, a total of 24 bits are generated. Subsequently, the range lies between 24–32 bits for other samples. The average CR for the compression system is found to be 2.75, and the maximum CR is found to be 3.14. With a power consumption of 2.9 W., Around 92% of the power is utilized in I/O operation from memory to fetch the data, which can be reduced in the actual design because real-time data is acquired in the latter case, as seen in Figure 3. The logic power utilization is 0.2W for the logical operations performed in the compression system. The total number of Lookup tables (LUTs) used is 408, and the flip flops used are 51. Table 1 shows the summary of results.

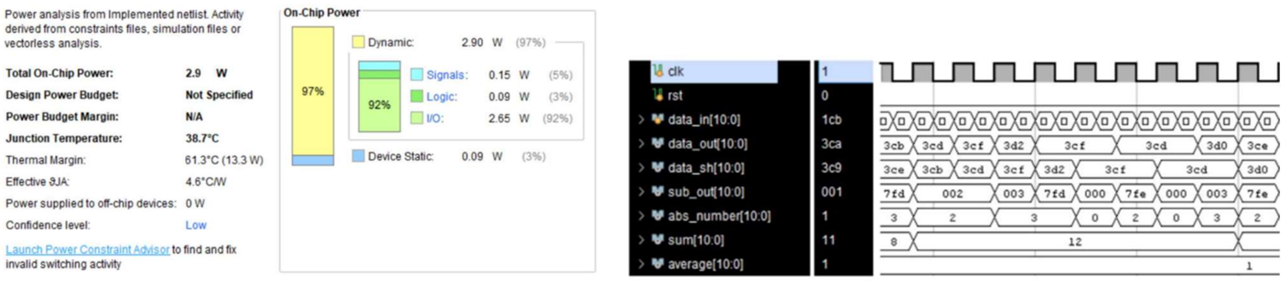

Figure 3. Power report and outputs of various subsystems.

Table 1. Summary of Results.

Metric	Value
Board Used	• Family: Artix-7 low voltage • Package: csg324 • Part number: xc7a100tlcsg324-2L
Mean CR	2.89
Highest CR	3.6
Lookup Tables used	408
Flip Flops used	51
Power (logical, I/0)	0.2 W, 2.7 W
Delay	7.2 microseconds

5. Conclusion and Future Scope

In this paper, a lossless ECG data compression system is presented. The compression system uses the Golomb Rice coding method to encode the ECG signals. MIT BIH arrhythmia dataset is used, which contains 11-bit raw ECG sample values. The CR attained by the compression system is 2.89 and 3.6 for average and maximum values. The design implementation is tested on Nexys DDR4 FPGA, which is of family Artix-7 low voltage. The design consumes 408 LUTs and 51 FFs at a clock frequency of 0.5 KHz. The system's logical power consumption is 0.2 W, and the I/O consumption is 2.7 W. It is observed that there is a trade-off between the transmitted power and the processing power in the sensor node if we aim to decrease the power consumption due to the transmission of extensive data.

Table 2 shows the comparison between different ECG compression techniques. The achieved compression ratio results in less energy requirements to send data and less storage space required, which helps achieve two critical wearables metrics, i.e., power and memory management, which helps in the development of a better and optimized wearable system. Additional computations must be done via the processor used in the sensor node. However, due to the advances in VLSI technology, the processor design is highly optimized and can provide better savings. The implemented compression system can further be extended for physical design implementation. The changes at this step, like clock gating, power gating and algorithmic level changes, can further reduce the system's power consumption. The proposed system can also be modelled for sensor node simulations to map the power saving due to the compression methods applied. The system can also be used for various biomedical signals for data compression.

Table 2. Comparison of Results**.**

Parameter	This Work	2020 [19]	2017 [18]	2017 [16]	2017 [15]	2016 [17]
Method	Golomb Rice Encoder	Lossless ECG Compression	Wavelet Shrinkage	Entropy Coding	Context-Aware Compression	Joint Coding Package
Compression ratio	2.75	2.77	2.70	2.15	2.15	2.1

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