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A VLSI-Based Multi-Level ECG Compression Method forHealth Care Applications

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Abstract: *Wearable sensor nodes generate a lot of data since they have characteristics for continuous monitoring. Additionally, as data transmission uses around 3/4 of the sensor node's power, power consumption is a significant barrier to these nodes' ability to maintain longer battery life. Wearable sensor nodes create and send a considerable quantity of data during intelligent long-term monitoring of any biological signal in wireless body area networks, boosting transmission power consumption. A lossless data compression method for an ECG signal monitoring system is suggested in order to decrease data storage and power use. In order to improve the bit compressing rate, a hybrid lossless multi-level compression technique based on Golomb-Rice coding and dictionary selection based on bitmask approach is presented. The majority of lossy techniques require an efficient preprocessing stage in order to identify the clinically important attributes with the lowest reconstruction error. As a result, computational workload increases. Furthermore, moving across domains requires a large storage space with a larger latency. In lossless compression, prediction-based methods utilizing Golomb-Rice encoding are employed. putting into practice an adaptive linear predictor and recording the projected difference with varying length.The implementation of adaptive Golomb-Rice entropy coding in an adaptive linear predictor built on VLSI is explained. Using a power-gating technique, compressed sensing develops a low-power FPGA-based compression architecture.*

I.INTRODUCTION

In order to find the clinically significant characteristics with the lowest reconstruction error, the majority of lossy approaches need an effective preprocessing stage. Consequently, computational burden rises. Additionally, switching from one domain to another increases the latency and necessitates significant storage capacity. Prediction-based approaches using Golomb-Rice encoding are used in lossless compression. Predicted difference is encoded with variable-length encoding using an adaptive linear predictor. This shows how to implement adaptive Golomb- Rice entropy coding in a VLSI-based adaptive linear predictor. Compressed sensing uses a power-gating technique to create a low-power FPGA-based compression architecture. These approaches involve computationally demandingprocedures, which have an impact on the area overhead and power consumption of the wearable node. The VLSI- based lossless compression techniques with optimal area overhead and power consumption are in great demand for real-time, online application on the wearable sensor node for biomedical signal monitoring. To enhance CR,however, requires more research, and as the amount of sent data increases at the sensor node, the battery's lifespan decreases noticeably.

Electrocardiogram

The technique of electrocardiography involves creating an electrocardiogram (ECG or EKG), which is a recordingof the electrical activity of the heart. It is a heart electrogram, which uses electrodes applied to the skin to create a graph of voltage vs time for the electrical activity of the heart. These electrodes pick up the minute electrical alterations brought on by the depolarization and repolarization of the cardiac muscle during each cardiac cycle (heartbeat). Numerous cardiac abnormalities, such as irregular heartbeat (such as atrial fibrillation and ventricular tachycardia), insufficient coronary artery blood flow (such as myocardial ischemia and myocardial infarction), and electrolyte disturbances (such as hypokalemia and hyperkalemia), cause changes in the normal ECG pattern.

Traditionally, "ECG" has referred to a 12-lead ECG that was recorded while laying down, as explained below. While certain versions of smart watches may also record an ECG, other devices, like a Holter monitor, can capture the electrical activity of the heart. ECG signals may be captured using different tools in different situations.

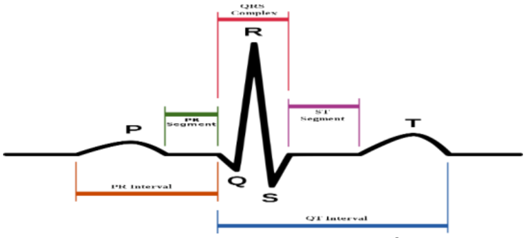

Figure1.1 Standard ECG Wave form

The P wave, which indicates depolarization of the atria, the QRS complex, which shows depolarization of the ventricles, and the T wave, which represents repolarization of the ventricles, are the three primary elements of anECG.

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IoT healthcare platform

Medical gadgets with ultra-low power consumption are essential in the internet of things (IoT) age. Vital physiological information is captured by healthcare sensors for patient monitoring and diagnosis. Holter monitorsare limited by power consumption since they continuously record and monitor electrocardiogram (ECG) data for 24 hours. As opposed to holter monitors and other comparable devices, IoT healthcare solutions permit little local processing and transport data to cloud-connected servers. There have been several proposed IoT systems for the healthcare industry. According to the theory depicted in Fig. 1.3, IoT healthcare links patients, physicians, and devices. IoT infrastructure includes anything from sensors, communication tools, to central servers that haveefficient devices built in. System engineering problems, which include signal collecting, local processing, transmission, central processing, and feedback generation, extend to IoT platform challenges.

Fig. 1.2. IoT healthcare platform.

With more connected gadgets on the market, each of these stages faces unique difficulties. 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 detection. As a point of reference, the depolarization of the heart's ventricles is represented by the QRS complex, a crucial part of the cardiac cycle. For normal beats, its amplitude increases to 1 or 2 mV above or below the isoelectric line, and for irregular beats, it can increase multiple times. The QRS width or interval, which normally 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, establishing the precise location of the QRS complex in ECG signal processing is essential for automatic ECG delineation approaches. Different signal processing methods for QRS detection have been put out in the literature and will be briefly discussed. Algorithms for QRS detection are incorporated intowhole systems, including analog fronts, in IoT medical equipment. More than 80% of the total power usage is attributable to the digital circuit used for QRS detection's power dissipation. Although IoT systems include transmitters with many Watts of power, they are only turned on briefly. In the order of nW, ultra-low power ECG analog-front end might be achieved, and 3nW ECG front-end is reported. At 187.5 kbps, the transmitter's power is

4.18 W. The power needed to extract energy from thermal or solar sources might be as high as 100 W. In recent work on biomedical SoC, a multi-sensor platform for ECG and other signals has been developed. The SoC's additional benefit of multiplexing numerous workloads made it small and suited for ultra-low power applications. The extracted characteristics from the IoT platform's IoT platform or the processed ECG data are frequently transmitted wirelessly. The IoT device's wireless data transfer is the most energy-intensive component.

II.LITERATURE REVIEW

1) VLSI implementation of lossless ECG Compression Algorithm for Low Power Devices

This work proposes a lossless ECG Compression Algorithm for electrocardiogram (ECG) data encoding to minimize transmission time and conserve storage space. Memory-less architecture has been used to take advantage of compression algorithm's ability to conserve store space and cut down on transmission time. This paper demonstrates a high clock speed VLSI implementation of an effective lossless compression method. A content- adaptive Golomb Rice code plus an adaptive linear prediction approach make up the ECG compression algorithm. The implementation of a compression algorithm on a VLSI chip has been shown to be effective and low power. The suggested VLSI architecture replaces the various arithmetic processes with bit shifting operations to increase performance. The MIT-BIH arrhythmia database has undergone VLSI implementation, which results in a lossless bitcompression rate of 2.77. Additionally, the VLSI design has 3.1 K gates and the chip's core uses 27.2 nW of power while operating at 1 KHz. The 90 nm CMOS process has a 0.05 mm 2 core area.

2) VLSI Implementation of Multi-Channel ECG Lossless Compression System

The electrical activity of the heart is captured using an electrocardiogram (ECG). Long-term signal monitoring will generate a lot of data from the device. Consequently, a successful lossless ECG compression method can aid in reducing storage space. The hardware design of a multi-channel lossless ECG compression system is shown in this book. The method used by the system includes both adaptive and multi-channel linear prediction. Additionally, entropy coding employs the Golomb rice code (GRC). The hardware implementation was created to utilize the least amount of hardware complexity possible. Additionally, the design may handle many channels simultaneously to achieve a high throughput. For purposes of testing and verification, the PTB database has been used. TSMC 180nm was used to implement this design. According to the implementation findings, the operating frequency is 1 KHz, the gate count is 476K, and the power consumption is 69.18W.

3) A 2.63 µW ECG Processor with Adaptive Arrhythmia Detection and Data Compression for Implantable Cardiac Monitoring Device

We offer a long-term implanted cardiac monitoring (ICM) device for arrhythmia diagnosis that uses an ultra-low power ECG processor ASIC (application specific integrated circuit) with R-wave detection and data compression.To detect arrhythmia with sporadic aberrant heartbeats, a low computation overhead adaptive derivative-based detection technique for possible arrhythmia recording is presented. A hierarchical data buffer structure is proposed which saves three types of data, including the raw ECG data segments of 2 seconds, compressed ECG data segments of 45 seconds, and R-peak values and interval lengths of >2000 beat cycles, in order to save as much cardiac information as possible with the limited memory size available in the ICM device. For the ECG data compression,a modified swinging-door-trending (SDT) approach is suggested. In order to achieve low dynamic power consumption and leakage, the ASIC was constructed based on entirely tailored near-threshold standard cells employing thick-gate transistors in 65-nm CMOS technology. Die area for the ASIC core is 1.77 mm2. One of the ECG processors with the lowest core power consumption has a measured total power of 2.63 W. In contrast to other systems in the literature with the same core power consumption level, it has a surprisingly high positive precision rate (P+) of 99.3% with a sensitivity of 98.2%. Additionally, a reasonable balance between compression efficiency and loss has been established, resulting in an ECG data compression ratio (CR) of up to 17.0.

4) Lossless and Lossy Direct Compression Design with Multi-Signal Symptom Detection for Low- Temperature Wearable Devices

In this study, the lossless and lossy direct compression (LLDC) approach is recommended for wearable technology. The electrocardiogram (ECG), blood pressure (BP), and respiration (RESP) can all be utilized in conjunction with the compression design for cardiovascular problems. The proposed LLDC can dynamically transition between various sampling intervals and data precisions and may detect abnormal symptoms. In our research, 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 energy of the wearable devices for ECG, BP, and RESP are decreased by 50%-87%, 38%- 89%, and 41%-89%, respectively, while the temperatures are decreased by 2.6°C-4.2°C, 1.3°C-3°C, and 1.7°C- 3.6°C.

5) Exploiting similar prior knowledge for compressing ECG signals

When sending electrocardiogram (ECG) signals in wireless body area networks (WBAN), data compression techniques have been employed to save power. Among these methods, compressed sensing enables the encoding of sparse or compressible signals with a minimal number of samples. Despite not being sparse, ECG signals can be rendered sparse in another domain. There are several sparsifying methods, however when signal quality and energy use are crucial, the current methods can be improved.

6) A 3-Lead ECG-on-Chip with QRS Detection and Lossless Compression for Wireless Sensors

This concept for a low-power, three-lead electrocardiogram (ECG)-on-chip for wearable wireless ECG sensors includes real-time QRS detection and lossless data compression. Up to two to five times less sensor power can be used using data compression and QRS detection. A circuit that does both lossless data compression and QRS detection enables various functions to share computing resources, which reduces the total system power. On common test data, the suggested method yields an average compression ratio of 2.15 times. When evaluated with the MIT/BIH database, the QRS detector obtains a sensitivity (Se) of 99.58% and a positive productivity (+P) of 99.57% @ 256 Hz. With a core size of 1.56 mm 2 and implementation in 0.35 m process, the circuit for two-channelECG compression and QRS detection uses 0.96 W @ 2.4 V. The chip is appropriate for use in wearable/ambulatory ECG sensors due to its small size and extremely low power consumption.

III. METHODOLOGY

Lossless compression scheme

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 determined D(n) revolve about zero. It displays the histogram of D(n) values for 10 ECG signals, each lasting one minute, from the MIT-BIH database. However, in other areas, a typical ECG signal is made up of amplitude fluctuations that correlate to peaks like the P-wave, R-peak, and T-wave. The D(n) values for various locations vary as a result of this amplitude change. With and without preprocessing, the suggested technique has been evaluated on digitized input ECG signals. The flowchart depicted in Fig. 3.1 summarizes the suggested lossless compression method. The evaluation of the first derivative D(n) from theprovided digitized ECG data serves as the basis for the compression approach.

$$D(n) = xn - xn-1. \quad (1)$$

$$M = 1/8 \times \text{summation of } (i+7 \text{ to } j=i)\ |D(n)|j. \quad (2)$$

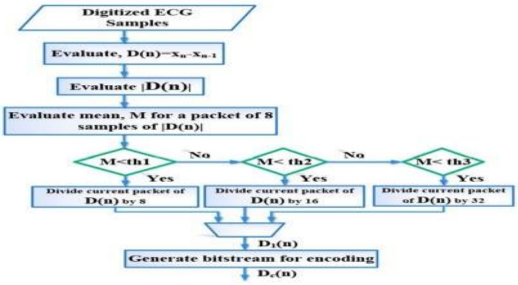

Fig.3.1 Flowchart of proposed lossless compression scheme

The three predetermined threshold values are then compared to the computed mean of each packet. These values are determined by accounting for the possible maximum of the |D(n)| samples that correspond to the low-amplitude, medium-amplitude, and high-amplitude areas, respectively, where th3 > th2 > th1. Based on the range of M, three unique divisors are determined, as shown in Fig. 3.1. After creating bitstream D1(n), the encoder generates compressed bitstream Dc(n).

Encoding

One of the effective lossless coding methods that has been applied when the input bitstream's amplitude values are much lower is golomb-rice coding. In Golomb-Rice coding, the quotient and remainder are determined by a divisor parameter of 2's power. The remainder and quotient are encoded in binary and unary formats, respectively. A stop bit clearly distinguishes the remainder from the quotient, and the bitlength of the remainder depends on the divisor. The adaptive region-based divisors, which may be written as a power of 2, are best suited for Golomb-Rice coding since the amplitude of the ECG is already suppressed by the calculation of D(n). From a hardware standpoint, Golomb-Rice coding using these particular divisors is simple to implement and doesn't require a lot of expensive hardware. The remainder and quotient are shown as follows:

$$\text{Quotient} = [D(n) / 2\text{^}k] \ , k = 3, 4, 5 \ (3)$$

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

VLSI Hardware architecture

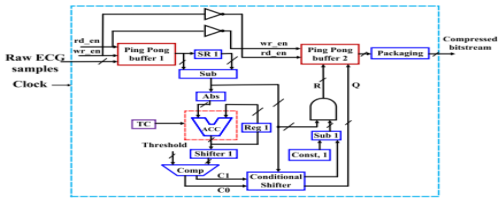

Fig. 3.2 Block diagram of the hardware architecture

This section talks about the suggested algorithm's hardware implementation. Figure 3.3 displays the suggested design at the block level. It shows how compressed data is produced from ECG sample data and then packaged. The stream of digitized input data has 11 bits per sample. The packets are kept in ping pong buffers that are 11 x 8. The signals "wr_en" and "rd_en" allow for writing to and reading from the buffers, respectively. The data are initially retrieved using a shift register (SR 1), and then the "sub" block subtracts the data as specified in (1) to produce the first-order derivative, or D(n).

Proposed Multi-level ECG compression Architecture

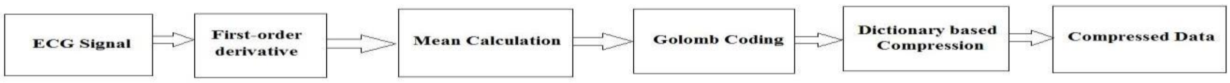

Fig. 3.3 Proposed block diagram

Run-length encoding

Data runs (sequences in which the same data value appears in several consecutive data elements) are kept as a single data value and count rather than as the original run in run-length encoding (RLE), a type of lossless data compression. The most effective data for this are those with a large number of these runs, including basic graphic pictures like icons, line drawings, Conway's Game of Life, and animations. RLE could increase the file size for files with few runs.

Think of a screen with solid white backdrop and simple black lettering. In the empty space, there will be several long lines of white pixels and numerous small runs of black pixels. A hypothetical scan line would look like this: B represents a black pixel, while W represents a white pixel.

WWWWWWWWWWWWBWWWWWWWWWWWWBBBWWWWWWWWWWWWWWWWWWWWWWWWBWWWWWWWWWWWWWW

The above-mentioned hypothetical scan line can be presented as follows when a run-length encoding (RLE) data compression method is used:

12W1B12W3B24W1B14W

The original 67 characters are condensed into only 18 by using a series of twelve Ws, one B, twelve Ws, three Bs, and so on. Although binary data is typically used to store pictures rather than ASCII letters like these, the idea is the same. This technique may be used to compress even binary data files; file format specifications frequently provide repeated bytes in files as padding space.

Golomb Coding

One of the lossless data compression methods is golomb coding. It has the ability to reduce the amount of bigger data while maintaining the ability to recover the original data after decompression. Arithmetic coding and other high performance lossless compression algorithms are also available. However, the computational load and design complexity of this technique are higher.

Data set	01 0000001 0001 000001 001 1					
Subset	01	0000001	0001	000001	001	1
Run-length	1	6	3	5	2	0

Table 3.1. Determination of run-length

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

Table 3.2. Golomb coding example with parameter m = 4

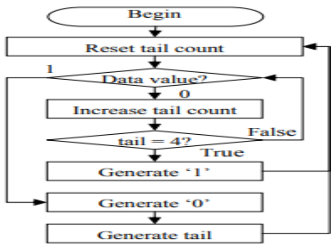

Figure 3.4. Golomb encoder algorithm (parameter m=4)

The flow chart in Figure 3.7 can be used to explain the Golomb encoder concept. The proportion of '0's in the incoming data determines the tail count. When reading '0's, the tail count will rise correspondingly until it exceeds the m parameter, at which point a '1' will be produced as the output data. The algorithm 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 waits for the next input of data before restarting the tail count.

Dictionary-Based Approach

Dictionary-based code-compression methods offer effective compression and quick decompression mechanisms. The fundamental concept is to use a dictionary to exploit frequently occurring instruction sequences.

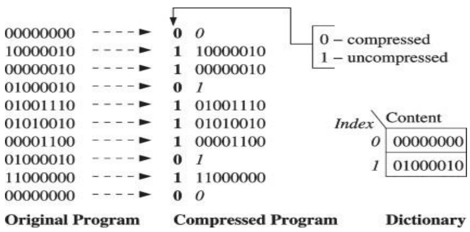

Fig. 3.5. Dictionary-based code compression: an example.

Enhanced Dictionary-Based Method By taking mismatches into account, two recently proposed approaches [3], [4] enhance the traditional dictionary-based compression method. Finding instruction sequences that differ by a small amount of bit positions (Hamming distance) and storing that information in the compressed program along with any necessary dictionary updates is the main principle. The number of bit changes taken into account during compression will determine the CRs.

IV. SOFTWARE DISCRIPTION

Verilog HDL

Verilog is a HARDWARE DESCRIPTION LANGUAGE (HDL). A hardware outline Language is a language used to describe a digital system, such as a flip-flop, memory, or microprocessor. This simply means that one may describe any hardware (digital) at any level using an HDL.

XILINX ISE DESIGN SUITE

The design may be input using graphical schematics, state machine diagrams, VHDL, and Verilog thanks to the Xilinx ISE tools. The whole design flow is managed by the ISE®Design Suite. You have access to all of the design entry and design execution tools through the Project Navigator interface.

MODELSIM

Mentor Graphics' ModelSim is a multi-language HDL simulation environment with a built-in C debugger for simulating hardware description languages including VHDL, Verilog, and SystemC. You can use Altera Quartus or XilinxISE in addition to or instead of ModelSim.

The graphical user interface (GUI) or automatically running scripts are both used to carry out simulation. Large multi-million gate designs employ ModelSim SE, which is available on Linux and Microsoft Windows in both 32- bit and 64-bit architectures.

V.RESULT

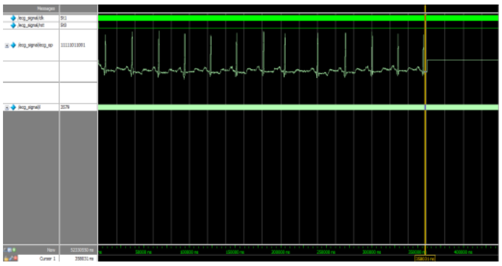

Fig. 5.1 Simulation result of input ECG signal

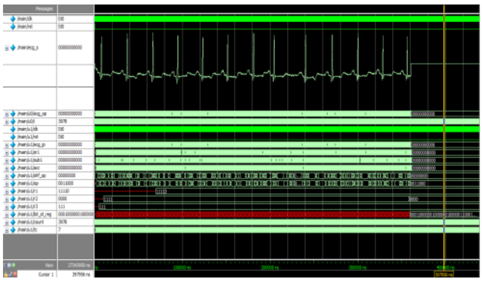

Fig.5.2 Simulation result of the existing method

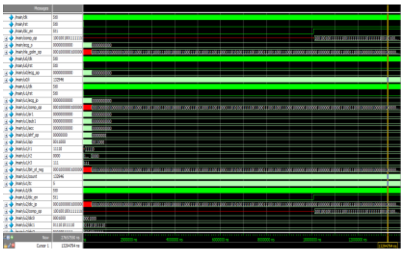

Fig. 5.3 Simulation result of the proposed method

VI.CONCLUSION

The proposed work demonstrates an on-node hybrid lossless ECG compression architecture for sensor nodes that can improve CR. The proposed compression scheme is compatible in sensor node, achieving good CR. Further, multi-level compression scheme based on runlength, golomb and dictionary selection helps in achieving efficient compression. The proposed architecture consumes low power power at 100 MHz operating frequency. Nominal power consumption and area overhead with maximum operating frequency of 250 MHz make the proposed architecture compatible in miniaturized sensor nodes. Besides, 6% of the transmission power has been saved in this transmission mode over uncompressed ECG for a transmission period of 1 min. The proposed scheme can be furtherstretched for other biomedical signals.

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