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Multi-channel ECG Lossless Compression System

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ABSTRACT: The electrical activity of the heart is recorded by an electrocardiogram (ECG). When an instrument monitors a signal for a long time, it generates a lot of data. As a result, the efficient lossless ECG compression technique can aid in the reduction of storage space. The hardware architecture of a multi-channel lossless ECG compression device is described in this research. The system is based on a multi-channel linear prediction and adaptive linear prediction algorithm. Entropy coding is also done with the Golomb rice code (GRC). The hardware implementation was created with a minimum level of hardware complexity and the most efficient use of hardware resources. Furthermore, the architecture may process many channels in parallel, resulting in high throughput. The PTB database was utilized for verification and testing. This design was made in TSMC's 180nm process. The gate count is 476K, the power consumption is 69.18W, and the operating frequency is 1KHz, according to the implementation results.

KEYWORDS - Hardware, Golomb Rice Code, ECG Compression

I. INTRODUCTION

The electrocardiography (ECG) signal depicts electrical activity in the heart. ECG signals have been utilised in medical research for many years to examine and improve therapy of cardiac problems [1]. The subject of ECG signal compression is addressed in this thesis. Our goal is to create an algorithm that can achieve a high compression ratio while maintaining a high level of quality. The rationale, contributions, and arrangement of the thesis are detailed in this chapter.

The ECG signal displays, among other things, the speed and regularity of heartbeats, which are important indicators of cardiac activity. The PQRST complex [2], which was established to describe the normal ECG cycle in the early twentieth century, achieved significant development. It simplifies analysis by using capital letters to name each part of the usual waveforms/deflections. PQRST complex combinations might suggest a variety of cardiac activities; for example, a short QT interval could indicate hypercalcemia, which causes an abnormal heart rhythm [3]. Figure 1 depicts the PQRST complex of a typical ECG cycle.

A modern ECG monitor consists of a variety of hardware components and functions. IMEC-NL [4] provided an example, where a mixed-signal SoC was built to serve a variety of ECG signal applications. Despite the fact that there are a number of challenges with portable ECG monitors, such as size, speed, and cost, the storage limit and transmission capacity stimulate the development of ECG signal compression. ECG signals that have been stored are shown in digital format. ECG signals have a resolution of more than 10 bits per sample, and the sampling frequency can be as high as 512 hz. This means that a single minute of real-time storage needs 37.5 kB of RAM. The bit representation of the original signal will be a massive storage burden. Furthermore, transmission costs a significant amount of energy.

ECG signal compression is possible due to the regularity of ECG signals: reliable ECG records are approximately periodic, implying that redundancy is almost guaranteed. Because correlations between each cycle can be used and various prediction systems can be used, this trait is advantageous for compression. Furthermore, ECG signals are frequently restricted to a specific frequency range. The best compression ratios are likely to come from frequency domain transforms. Existing transform-based compression algorithms, such as the JPEG standard [5] for image processing and MPEG compression [6] for audio processing, have demonstrated success and efficiency in a variety of signal processing applications. Both of these transform-based methods are commonly utilised today.

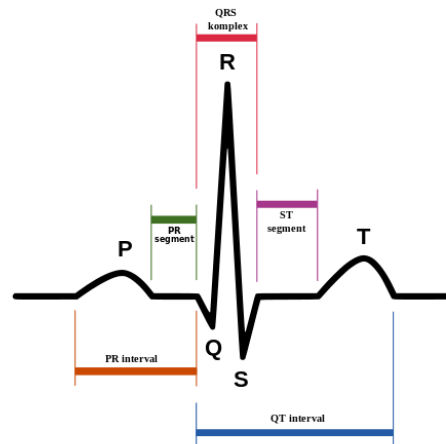


Figure 1: Schematic diagram of normal sinus rhythm for a human heart as seen on ECG[7]

II. RELATED WORKS

Lossless ECG compression has been the subject of much research in the past. The prediction and entropy coding elements of a typical ECG compression technique can be separated. Regular prediction technique is one of the most popular ways to use prediction techniques. Lossless ECG compression relies on entropy coding as its foundation. Several varieties of ECG compression algorithms have been proposed in literature.

E.Chua and Wai-Chi Fang[8] proposed Mixed bio-signal lossless data compressor for portable brain-heart monitoring system. Their study described VLSI implementation of a mixed bio-signal lossless data compressor capable of handling multichannel electroencephalogram (EEG), electrocardiogram (ECG), and diffuse optical tomography (DOT) bio-signal data for reduced storage and communication bandwidth requirements in portable, wireless brain-heart monitoring systems used in hospitals or at home.

C.J. Deepu and Y. Lian [9] proposed a low complexity lossless compression scheme for wearable ECG sensors. They presented a method for compressing ECG in real time and zero lossless decompression using a combination of three different processes to increase storage space while reducing transmission time. G.A.Luo, S.L.Chen and T.L.Lin proposed VLSI implementation of a lossless ECG encoder design with fuzzy decision and two-stage Huffman coding for wireless body sensor network. An efficient VLSI design of lossless electrocardiogram (ECG) encoder is proposed for wireless body sensor networks. To save wireless transmission power, a novel lossless encoding algorithm has been created for ECG signal compression.

In their algorithms [10] and [11] provide a discussion of numerous lossless compression approaches. Chen et al. suggested an FPGA-based ECG compression algorithm based on variation separation and zero run-length coding [12]. Dora et al. [13] provided another FPGA-based method that used modified convolution and discrete wavelet transform. Chen et al. [14] present another VLSI architecture with a new adaptive rendering predictor and a two-stage entropy encoder. Simple arithmetic units can be used to create this ECG encoder. N.Attarmoghaddam [15] proposed a hardware design for compressed sensing ECG compression. They additionally offer a CS design that incorporates power gating to minimize power consumption.

III. METHODOLOGY

Many technologies have been developed in the medical field to obtain information about the many organs of the human body. The electrocardiogram (ECG) data is one of the purposes of such a system. These signals are commonly used in the investigation of various diseases and health-care issues. Many patients' ECG data must now be kept for an extended period of time. Because it would be continuously creating ECG data, compression will be required to reduce data storage space. A good compression system compresses data in real time while keeping the compression ratio high.

The goal of this project is to create a multi-channel ECG compression algorithm using 12-channel input data. Some major elements in this system include linear prediction, adaptive linear prediction approach, and Golomb rice

coding (GRC). Forward samples from the original data were employed to eliminate duplication in the prediction section, which resulted in a better prediction error than increasing the compression rate. The GRC is also used for entropy coding.

A predictor and an encoder make up the proposed lossless ECG lossless compression technique. The encoder receives the predictor's output as its input. The predictor contains multi-channel linear prediction and adaptive linear prediction, both of which are intended to boost entropy coding efficiency. Golomb-Rice coding is used to implement the entropy encoder.

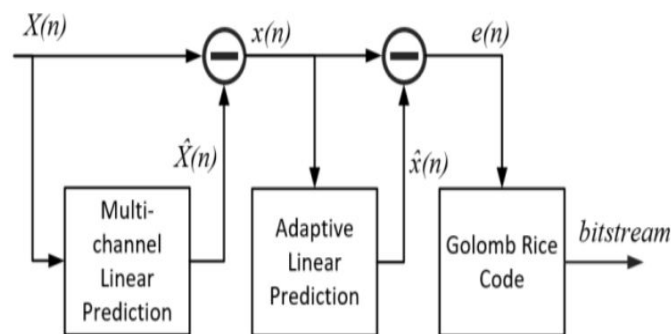


Figure 2: Block diagram of the proposed system

Multi-channel Linear Prediction

A 12-lead ECG was employed. The multi-channel linear predictor receives this data as input. These are values in 16-bit format. This information is analyzed, and a prediction value is determined for each channel. It can effectively minimize the correlation of each channel. After that, the prediction value is subtracted from the channel's original value using

$$x_p(n) = Xp(n) - \hat{Xp}(n)$$

where $\hat{Xp}(n)$ is the prediction error of n-th sample and Xp is n-th sample from prediction channel.

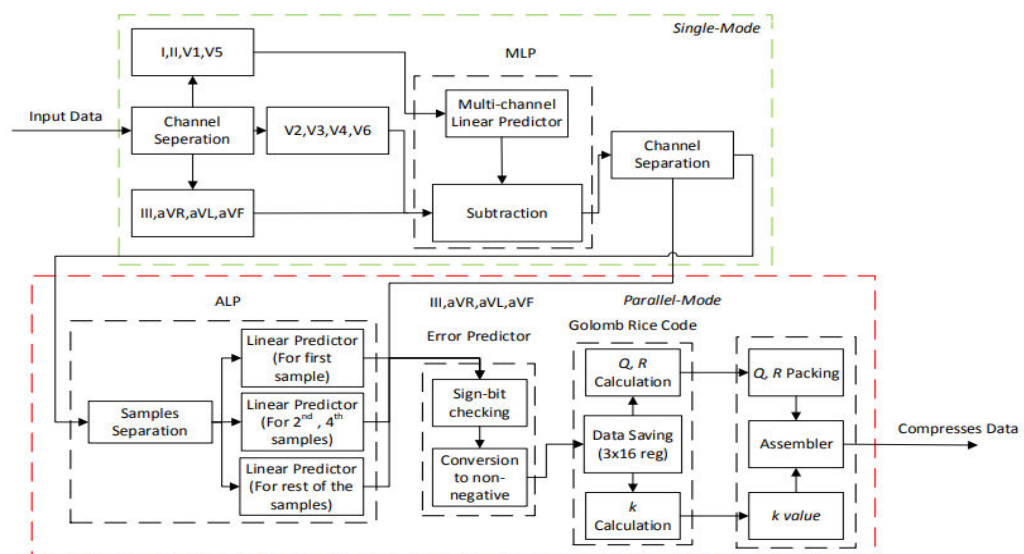


Figure3: Overall architecture flow

Adaptive Linear Prediction

The P, Q, R, S, and T waves are all present in the ECG signal. These regions are the source of a lot of forecast mistake. In order to maximise the efficiency of the algorithm and lower the overall prediction error, Adaptive linear prediction employs fuzzy theory and the exponential weighting technique.

Multi-channel Linear Predictor values are sent via an adaptive linear predictor. The input data values are separated and transferred to the appropriate predictors using a channel separator in ALP. After the data processing in the ALP module, error prediction is performed. The magnitude of the number is used to anticipate error.

Linear Prediction is performed using the below equation

$$\hat{x}_i(n) = \sum_{i=1}^m a_i x(n-i)$$

where $\hat{x}(n)$ is the prediction value of $x(n)$, m is the order of predictor and a_i is the coefficient.

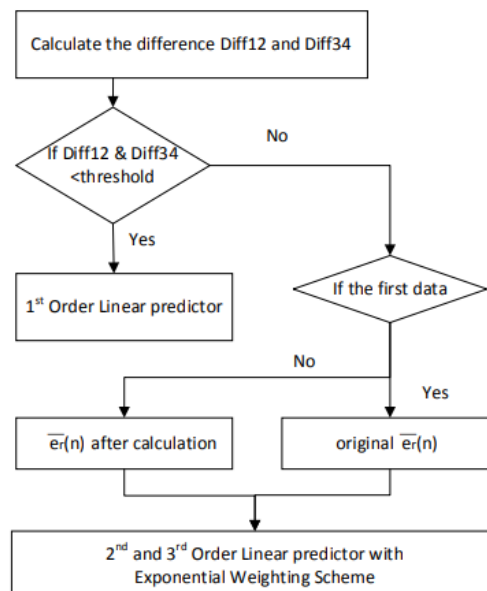


Figure4: Flow chart of Adaptive Linear Prediction

Three different predictors, which include 1st, 2nd and 3rd order predictors, are used to improve the prediction performance at different regions. These predictors are as follow:

1st order: $\hat{x}_i(n) = x_i(n-1)$

2nd order: $\hat{x}_i(n) = 2x_i(n-1) - x_i(n-2)$

3rd order: $\hat{x}_i(n) = 3x_i(n-1) - 3x_i(n-2) + x_i(n-3)$

Golomb Rice Coding

Entropy coding refers to parallel bits, which are commonly seen in designs and rare double bits, and is an important coding process used in information pressure. Huffman coding, number juggling coding, run length coding and Golomb coding are popular lossless entropy coding strategies. In this system golomb rice coding has been used for entropy coding.

In 1960, W. Golomb developed Golomb coding, an information pressure method based on entropy encoding and geometric dispersion. In comparison to other tactics, geometric appropriation

is highly suitable for revealing expectation mistake with a larger possibility of smaller prediction blunder. A Rice code is similar to a Golomb code in that the tunable parameters are of two intensities. Because increase and division by two were achieved using a bit move operation, Golomb code is favourable to utilise on a computer. Furthermore, when compared to enormous qualities, the incidence of small qualities in ECG information is fully high, therefore Golomb code was really beneficial since it has an appropriate prefix code.

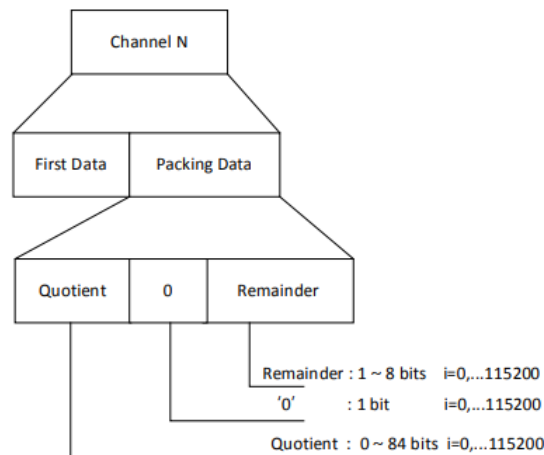


Figure5: Packing data format

In the next step, the residual set is created by subtracting the output of the multi-channel linear predictor from the output of the linear predictor. The following is a representation of it:

$$e(n) = x(n) - \hat{x}(n)$$

To obtain the final bitstream, entropy coding is applied to the residual set. GRC has been chosen for entropy coding. The tuning parameter in this coding is a power of two, which makes it efficient to use because multiplication and division can be achieved using bit shift operations.

GRC is made up of two parts: quotient and remainder, which can be calculated using the equation below.

quotient: $\left\lfloor \frac{M[n]}{2} \right\rfloor$ encode with unary code

Remainder: $[n] \bmod 2^k$ encode with binary code

where $M[n]$ is the positive integer and k represents the number of bits for remainder.

Figure 5 depicts our design's packing format. This rule will organise the data from each channel. The bitstream contains the initial 16 bits of Adaptive Linear Prediction data in order for the decoder to accurately generate the original data. For each channel, we'll organise the Q,R,K values generated by GRC in the form of 'Q0R.' We put one bit of '0' between both encoding values to identify the unary and binary codes during the decoding procedure.

Software Details:

Xilinx ISE

Xilinx ISE (Integrated Synthesis Environment) is a discontinued software tool from Xilinx for synthesis and analysis of designs. Xilinx Tools is a collection of software tools for designing digital circuits with Xilinx Field Programmable Gate Array (FPGA) or Complex Programmable Logic Device (CPLD) technology (CPLD). (a) design entry, (b) design synthesis and implementation, (c) functional simulation, and (d) testing and verification make up the design procedure.

The following CAD tools can be used to input digital designs in a variety of methods, including utilising a schematic entry tool, a hardware description language (HDL) - Verilog or VHDL, or a mix of both.

Verilog

Verilog is a Hardware Description Language (HDL). It's a programming language for defining digital systems including network switches, microprocessors, memory, and flip-flops. HDL can be used to describe any digital hardware at any level. HDL-described designs are technology-independent, simple to create and debug, and typically more useful than schematics, especially for large circuits. The Verilog HDL is the most widely used and practised HDL in the semiconductor industry. Verilog is a hardware description language like any other. It allows designers to create designs using either a bottom-up or top-down approach.

IV. RESULTS AND CONCLUSIONS

We compare the proposed compression algorithm to various state-of-the-art lossless approaches designed exclusively for ECG signals in this section. To be more specific, the following metrics were used to compare:

- *Compression Ratio (CR)* is the ratio of the number of bits before compression to the number of bits after compression.
- *Complexity*: We divided the algorithms into based on their complexity: Simple, Feasible, and Unfeasible. Simple algorithms are those that are based on linear predictors and encoding techniques and can be easily integrated in microcontrollers; feasible algorithms can also be implemented in microcontrollers, but they require more storage and computational resources; and finally, unfeasible algorithms are those that are too complex to be integrated with low-cost microcontrollers due to complex predictors or large memory requirements.

This project was set out to develop a practical ECG signal compression algorithm, which could maintain desired quality. Based on the transform-based compression scheme, the paper explored different methods to achieve a superior compression ratio. A multi-channel ECG lossless compression technique is proposed in this paper. The prediction part of this compression system is adaptive linear prediction, while the entropy coding part is Golomb rice code.

Solution	Chen [13]	Lian [9]	Luo [14]	Li [16]	Deepu [9]	Chen [18]	Garg [17]	Proposed
Actual CR	2.43	2.25	2.53	2.45	2.38	2.84	2.2	2.0
Predictor	Adaptive	First order	Fuzzy	Adaptive	Adaptive	Fuzzy/PSO	Adaptive	MLP, Adaptive
Entropy Encoder	Huffman (2-st.)	Dynamic Pack.	Huffman (2-st.)	VLC (1-st.)	Huffman (1-st.) + Dynamic Pack.	Huffman (6-st.)	Huffman (1-st.)	Golomb Rice Coding
Complexity	Simple	Simple	Feasible	Simple	Simple	Unfeasible	Simple	Simple

TABLE I

COMPARISON OF LOSSLESS COMPRESSION ALGORITHMS FOR ECG SIGNALS

Table 2 Size of ECG files according to their duration.

With the help of the proposed system the storage space required to store ECG files will be reduced significantly

V. CONCLUSION AND FUTURE WORKS

We offer a simple and effective lossless compression technique for ECG signals in this study. The approach outperforms multiple current solutions using only adaptive predictor and entropy encoding. It's also ideally suited for low-cost ECG monitoring systems based on resource-constrained IoT devices due to its intrinsic low complexity and memory requirement.

In future research, we'll look into how well the proposed algorithm performs with different types of biomedical signals.



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