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AN ENERGY AND AREA EFFICIENT IOT ARCHITECTURE FOR BIO-MEDICAL APPLICATIONS

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ABSTRACT

Heart Stroke, cardiac arrest are more prominent deceases assassinating the harmony of the people. Meticulous detection of the abnormalities and myocardial infarctions leads to abrupt change in the functionality of the heart. QRS Complex amplitude and R wave amplitude are significant to detect the abnormalities and sudden cardiac arrest. This paper focused to develop an architecture to meet the challenges of IOT enabled wearable devices. Absolute value curve length transform (A-CLT) is implemented to detect the QRS complex Changes. The proposed methodology nullifies the multipliers and performs well with adders, shifters and comparators. Eventually, the packing density (area) is minimized. This will improve the processing time and minimizes the dissipating power. This paper addressed the complexity in early detection of the strokes and cardiac arrests by analyzing the QRS complex of the ECG signal. Base line drift, high frequency interference (artifacts) are impacting on the signal generation. The proposed methodology curtails those artifacts and improves the performance of the signal detection and interpretation. The area is miniaturized with the A-CLT approach. 93.36 percent of the area is reduced with A-CLT. 77.61 percent of power is minimized with A-CLT methodology. The computation delay is reduced to 79.64 percent. This paper also addressed the sensitivity and predictivity of the QRS complex amplitude meticulously. 99.46 percent predictivity and 99.24 percent sensitivity is achieved with the proposed methodology. The achieved results are validated with the physician and specifically, achieved lossless compression for enhancing the derivative of ECG Signal and entropy encoding. It is observed that the compressed fraction is 2.05 and is validated with MIT-BIH database. The proposed methodology is surpassing the existing methods. The achieved results proved that this A-CLT applied architecture is best fit for wearable devices to prevent abrupt changes in cardiac functionality and to safeguard human from sudden cardiac arrests.

Keywords: *Absolute Value Curve Length Transform (A-CLT), QRS Complex, Quadratic Spline Wavelet Transform, Electrocardiography (ECG)*

1. INTRODUCTION

Biomedical devices, including telemedicine, wearable medical devices, and physiological parameter tracking systems, are using integrated circuit (IC) technology to meet the growing needs in healthcare devices. The implication of the new technologies are significant in research endeavors to enhance the functionality of medical devices. Ventricular arrhythmia is an irregular rhythm in electrocardiogram that leads to cardiac arrests specifically for who have cardiac related disorders. [1]. There are a number of factors that may lead to ventricular arrhythmias, the most common of which are coronary heart diseases, hypertension, and cardiomyopathy. Failure to properly identify or treat these conditions can result in significant patient mortality. Diagnostic methods such as long-term electrocardiogram monitoring can identify ventricular arrhythmia. Through the collection of precise data on the ECG signal intervals, amplitudes, and waveform morphologies of the distinct P-QRS-T waves, it is possible to make this determination. Furthermore, can make effective use of the same data for the purpose of predicting and identifying cardiac arrhythmia [3]. The Internet of things health care policy requires local processing of data before transmitting it to cloud-linked servers. This may aid in assessing holter monitor capabilities. The sources [4, 5, 6], and [7] address the different Internet of Things ideas, their implementations, and accompanying problems that are linked with them. The theory that underpins the architecture of the Internet of Things (IoT) infrastructure makes it possible to collect data from a variety of sensors that are embedded in communication devices and then transmit data to a central server that can integrate efficient devices. The QRS complex, a crucial element of the cardiac cycle, signals the depolarization of the heart's ventricles. Electrocardiogram (ECG) data analysis is done to precisely find the location of the QRS complex. This is needed for the development of automated ECG delineation techniques. To communicate ECG data, the Internet of Things platform relies mostly on wireless communication Technology. During the process of data transfer, this wireless technology consumes a significant amount of energy. More power dissipation takes place with serial communication to transfer the ECG related signals. The paper [8] proposes a low-power capacitive electrocardiogram monitoring system for wireless transmission.

2. RELATED WORK

In general, we can divide this subject into two groups. The most significant category revolves around the advancements in QRS detection methods. When it comes to QRS detection systems, the primary objective is to achieve high sensitivity and predictability while simultaneously reducing the amount of hardware resources required. The various strategies covered in this section utilize a variety of hardware implementations, including high-pass filters, low-pass filters, 3M filtering principles, wavelet transformations, and other approaches, to achieve varying degrees of sensitivity and predictivity. We will discuss the various developed compression strategies in the second part of this tutorial. Even though there were various artifacts present, the compression algorithms were able to effectively compress a wide range of morphological electrocardiogram (ECG) data. Because of this, it is possible to have more in-depth knowledge of earlier compression techniques. The wavelet transforms and the cross-wavelet transform are the foundations of the robust single-lead electrocardiogram system that we build in [9 and 10]. We use standard annotated datasets with a variety of sample rates to validate the method. We tested this method and found its sensitivity and predictability to be 99.66 and 99.56, respectively. The T wave component concludes with the most notable improvement. As far as I can tell, the implementation of a multi-scale technique, which enables the reduction of noise at rough scales and then attempts to increase the precision of the locations using finger scales, indicates a significant improvement.

We propose an ECG feature extraction scheme in [11, 12] that is well-suited for mobile healthcare applications. Reference [13] describes an integrated ECG signal-processing scheme that uses an SWT algorithm to do a number of real-time tasks, such as removing baseline drift, lowering noise, finding QRS, guessing heartbeat rates, and classifying heartbeats. This architecture integrates multiple high-pass and low-pass filters that facilitate the de-noising, compression, and reconstruction of ECG signals. Application-specific integrated circuits using 0.18m CMOS technology employ these filters. Experimental results demonstrate that this ECG signal processor exhibits low power consumption and minimal area requirements. This renders it suitable for the design of wearable applications with extended durability. Similarly, [14] describes the design of a CMOS low-pass filter that operates at ultra-low power levels, contributing to energy conservation. In references [15, 16], we present a novel ECG QRS recognition method for easy-to-wear ECG devices. This method uses multi-scale mathematical morphology filtering to find QRS, which effectively blocks out random noise, and multi-frame discrepancy modules to get rid of baseline drift, which improves the quality of the signal. The MIT/BIH database evaluates it, showing a detection rate of 99.61, a sensitivity of 99.81, and a positive predictive value of 99.80. Also, references [17 and 18] show how to make a low-power current mode analog QRS detection circuit and a signal regulating circuit that can be used for ECG applications that are worn on the body. In [19], we illustrate the QRS detection process utilizing the wavelet transform. The quadratic spline wavelet transform enhances QRS detection. Transform. In [20], we establish the foundational application of

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artificial neural networks for the detection and classification of ECG signals.

A 0.83-QRS detection processor has been introduced by [21] and is suitable for real-time wireless ECG monitoring. Using pre-filtering, feature extraction circuits, and dual-state machines that do maxima pair recognition with the Quadratic Spline Wavelet Transform (SWT) is possible. The MIT-BIH arrhythmia database evaluates the processor's performance, yielding a sensitivity of 99.31 and a predictivity of 99.70. Healthcare systems can effectively utilize the 120 nm design of Vivosoc [22]. A comprehensive analysis in [23] contrasts CS-based and DWT-based embedded ECG compression algorithms. This study demonstrates that compressive sensing (CS) compression is less effective than compression based on discrete wavelet transform (DWT). CS-based compression demonstrates energy efficiency and enhances execution time due to its reduced complexity. Promptly. This paper discusses the automatic computation of QT interval duration using body surface electrocardiograms (ECGs) as presented in [24]. We present the QRS detector design in [24]. Researchers have recently developed a new method for compressing ECG signals through the utilization of sparse features, intending to reduce power consumption [26].

3. PROPOSED SYSTEM

Two different modules are shown here. Both QRS detection architecture and variable-length compression are examples of different types of compression. Any system based on the Internet of Things (IoT) prioritizes data transmission after compression. The suggested work excludes data transfer due to issues such as transmission noise, mistakes, and other challenges. Additionally, the examination of transmission error relies on the selected transmitter and the specified protocol. The presented system provides an optimized QRS detection architecture that can handle all artifacts, requires minimal technology, and yields the most accurate results. The suggested method combines the pre-processing and transformation processes into a single stage, which ultimately results in a CLT that is efficient in terms of information processing. The CLT receives the QRS, a signal with a high slope and amplitude, from the ECG signal. The CLT receives a span of consecutive points from the ECG signal. Using this unique characteristic, the CLT enhances the QRS complex by suppressing other components of the electrocardiogram wave.

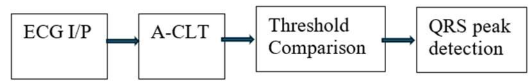

Figure 1: Block diagram of proposed architecture

Equation 1 displays the early CLT equation, also known as the Computational-CLT (C-CLT) equation. Equation 1 presents a challenging hardware implementation due to its requirement for addition, multiplication, and square roots. As a result, we rewrite the equation as equation 2, which we refer to as Squaring-CLT (S-CLT). Its huge amplitude ranges, on the other hand, make it difficult to implement, and the fact that it has a limited capacity to reduce baseline drift leads to a poor detection accuracy. Additionally, we modify it by replacing the square and square root functions in equation 1 with the absolute value function.

$$L(w,i)=\sum_{i=w}^{i}\sqrt{c^2+\Delta y_i^2} \quad (1)$$
$$L(w,i)=\sum_{i=w}^{i}c^2+\Delta y_i^2 \quad (2)$$
$$L(w,i)=\sum_{i=w}^{i}\left|c^2+|4*\Delta y_i|\right| \quad (3)$$

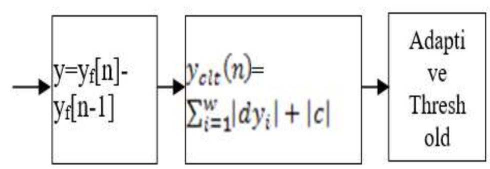

Figure 2: Proposed ACLT

The ACLT architecture that was used in order to acquire the QRS complex is shown in Figures 1 and 2, which were previously described. Within the context of this procedure, we carry out two tasks: the first one includes transformation, and the second one involves the detection of QRS peaks via the use of adaptive thresholding. In the process of transformations, we carry out integrations, derivatives, and absolute value calculations. The purpose of transformation is to eliminate the need for filters and solve the problem of handling all objects. Furthermore, it can identify R-peaks through comparison. Whether or not the integration is available, the system will process it to obtain a fresh electrocardiogram sample. The system currently operates at a sampling rate of incoming ECG signals, which makes duty cycling unfavourable.

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3.1 QRS Peak Detection by Adaptive Thresholding

For the purpose of identifying QRS peaks, we will now apply criteria. We will need to employ an effective method to analyze thresholds. We update the threshold using a method that considers the average of previously found R-peaks. The implementation of its circuitry is challenging, despite the fact that it provides 99% accuracy. Consequently, we implement equation 4, a method that modifies the threshold for each new sample and aligns it with the average of QRS peaks previously identified. Given the ease of dividing by eight through shifting and its straightforward implementation, we rely on eight previously identified peaks.

$$Th_i = Th_{factor} * mean \sum_{k=i}^{8} R_{peak} s_k \quad (4)$$

Identifying an appropriate threshold factor to manage diverse morphological variation. ECG waves from several databases are the most challenging aspect. But when we did tests on the MIT-BIH database, we found that for a certain window size, sensitivity goes up as the threshold factor goes down, and too much reduction may lead to false detection. Figure 3 illustrates the finite state machine (FSM) developed for the detection of QRS peaks. In State 1, it verifies if the ACLT signal is above the threshold. Initially, it establishes the threshold at fifty percent of the highest value of the first and second datasets, then uses equation 4 to adjust thresholds depending on newly identified beats.

Upon exceeding the threshold, a signal shifts to state 2, where it seeks the maximum values within a designated frame. This highest value indicates the position of the QRS peak. In state 3, the system produces a pulse to signify the identification of a new beat. The mechanism adjusts the pulse to counterbalance the peak value from state 2. Subsequently, the system resumes peak detection.

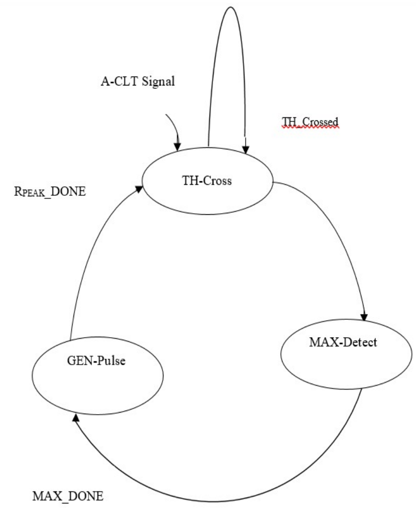

Figure 3: QRS detection FSM

3.2 Proposed ECG Compression Architecture

The original ECG is challenging to portray owing to its inherently enormous size, mostly attributed to the QRS complex, with almost all its values situated around the baseline. This requires an additional quantity of bits for representation. Our objective is to minimize bit overhead via the use of a derivative-based compression method. Used the first derivative to zero out the first and second derivatives. used adders to compute the first derivative. Executed the entropy encoder using combinational components such as comparators or priority encoders. A priority encoder needs less combinational logic for implementation over a comparator. Therefore, this paper used adders and priority encoders to accomplish the specified objective of compression. Figure 4 below shows how ACLT acquires the derivative. Figure 5 allocates the necessary bits according to the amplitude. It relies on amplitudes to reduce the total number of bits required to describe the entire ECG signal. The proposed design is appropriate for all wireless serial transmission modalities. Depending on the type of transmission, this paper incorporated an identifier to indicate the start and end of the identified variable-length data bits.

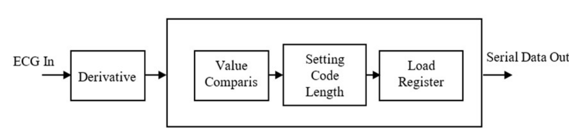

Figure 4: Proposed Compressor Architecture

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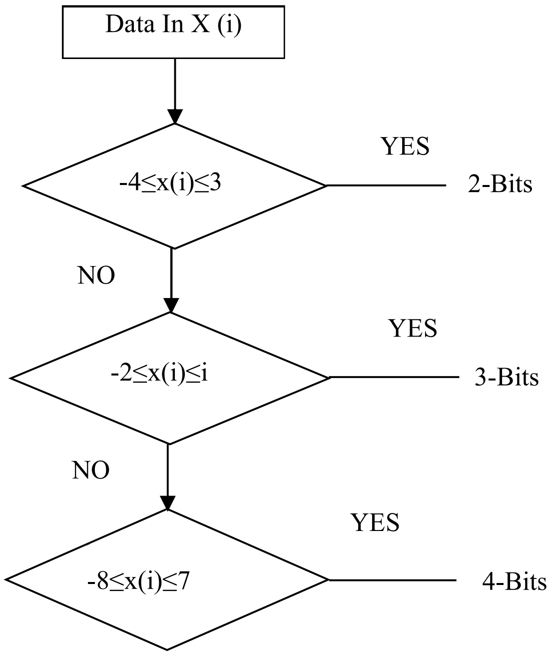

Figure 5: Entropy Encoder Flow Chart

4. RESULTS & DISCUSSIONS

This paper implemented the QRS-peak detection variable-length compression in VHDL. This study employs modalsim to derive conclusions related to functional verification. Variations in the area, power, and delay parameters, are observed but all QRS detection methods yield identical outputs.

The output of the implemented system is analyzed and compared its parameters with existing methodologies. Both analog and binary formats represent the ECG signal. This study focuses on two key components: ECG signal QRS-peak detection and variable length compression. Table 1 (and Fig. 6) below presents various performance parameters of both existing and implemented QRS detection techniques, evaluated according to their performance metrics: power, speed, and area. The ALT-based QRS detection scheme exhibits a power consumption of 7.19 nW, in contrast to the wavelet-based detection scheme, which consumes 9.274 nW. The data indicate that the ACLT-based QRS detection scheme exhibits a 22.38% increase in power efficiency relative to the wavelet-based ECG scheme. The A-LCT-based QRS detection scheme uses 15,095 gates, whereas the wavelet-based ECG detection scheme uses 16,167 gates, leading to a reduction in area overhead of approximately 6.67%. The computed delay for the ALCT-based QRS detection scheme is 15.193 ns, whereas the delay for the wavelet-based QRS detection scheme is 19.076 ns. This has led to a speed enhancement of 20.355% relative to wavelet-based detection.

Table 1: Comparison of performance metrics

Parameters	**Area (Gate Count)**	**Power (mW)**	**Delay (ns)**
Wavelet Based ECG Detection [13]	16,167	927.54	19.076
ACLT Based QRS Detection	15,095	719.94	15.193

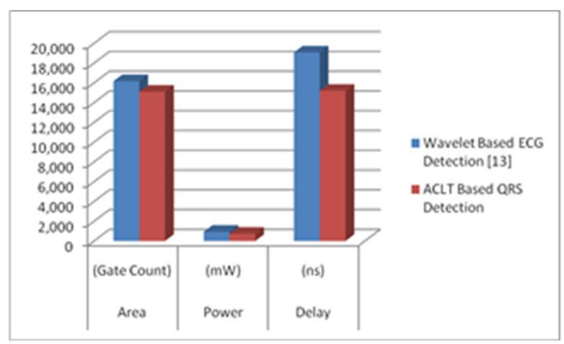

Figure 6: Comparison of performance metrics

Table 2: Comparison of Sensitivity and Predictivity

Technique	Sensitivity	Predictivity
[9]	99.72	99.85
[13]	99.56	99.82
[21]	99.45	99.22
Proposed	99.23	99.46

Table 2 (and Figure 7) displays the sensitivity and predictability of the implemented approach, along with the competing methods. The table provides an illustration of the suggested design, which achieves sensitivity and predictivity rates of about 99 percent, which are equivalent to those of its rivals. Table 3, in conjunction with Figure 8, provides a succinct overview of the computational components integrated into the developed architecture. Twenty memory cells and fifteen adders are the estimated hardware components that are necessary to implement the proposed

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design. On the other hand, the primary hardware components that are required to implement the architecture [20] consume thirty memory cells, eight multipliers, and three adders. The major source for decrease in area overhead and power consumption is application of Adaptive CLT technique that eliminates multipliers in the proposed architecture design. These figures demonstrate the implementation of the proposed architecture without the need for multipliers, which can help reduce power consumption and delay.

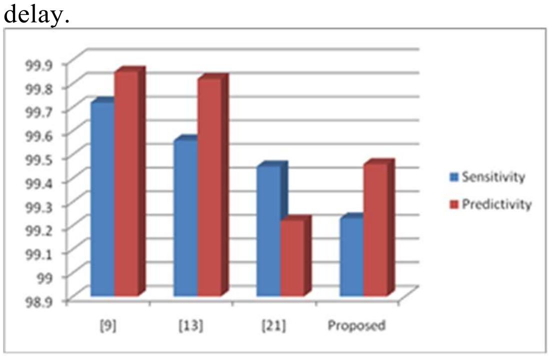

Figure 7: Comparison of sensitivity and predectivity of proposed, [9], [13], and [21]

Table 3: Hardware Requirements of Proposed method and existing method [25]

Type of component	[25]	Proposed
Memory Cells	30	20
Multipliers	8	0
Adders	3	15

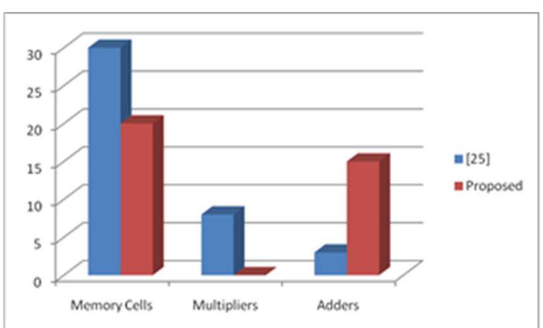

Figure 8: Comparison of hardware Requirements of proposed method and [20]

5. CONCLUSIONS AND FUTURE SCOPE

This research aims to create an energy-efficient architecture for IoT wearable devices. Specifically, to prevent cardiac arrests by detecting the QRS complex amplitude (peak). Compression architecture using A-CLT algorithm is applied to detect the variations of the QRS peak amplitude. The performance metrics like power consumption, area reduction and processing speed are evaluated in this paper. To minimize the area, approximately 1072 gates are reduced over existing methodologies. This paper focus to minimize bit overhead via the use of a derivative-based compression method. A priority encoder is used to minimize the combinational logic complexity. And to further minimize the combinational logic complexity adders and priority encoders used to accomplish the specified objective of compression.

The implementation of A-CLT, removes the multipliers in the proposed architecture, results area minimized to 93.36 percent. Owing to this area minimization, the power consumption is also significantly reduced to 77.61 percent. The adaptive technique, which emphasizes the energy level difference between consecutive levels, primarily facilitates speed enhancement. The implemented structure demonstrates a 20% improvement in processing speed compared to its counterpart. The exclusion of multipliers in ALCT notably enhances processing speed. The predictivity and sensitivity of the proposed architecture are 99.23 and 99.46. These values are relatively close to other existing methods.

The proposed architecture reduces complexity in hardware components by employing only 20 memory cells and 15 adders, and significantly removes the quantity of multipliers and reduces the memory cells.

The proposed architecture minimizes power consumption and area, and specifically enhanced speed of computation. The A-CLT applied architecture is compared with the wavelet-based detection algorithm. The A-CLT methodology reduces the delay of 79.64 percent over other methodologies. The compressed fraction observed is 2.05 and is validated with MIT-BIH database. The area overhead is reduced to approximately 6.67%. The estimated delay for the ALCT-based QRS detection is 15.193 ns.

The proposed methodology is surpassing the existing wavelet-based methods. The achieved results proved that this A-CLT applied architecture is the best fit methodology for wearable devices to prevent abrupt changes in cardiac functionality and to safeguard humans from sudden cardiac arrests. Further, this paper can be extended with imparting power-saving mechanisms such as voltage scaling and frequency scaling mechanisms to improve the low power consumption medical devices

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