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Analysis of K-RLE Data Compression Performance on ECG Signals for an Internet of Things Application

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ABSTRACT

A wireless biomedical monitoring system begins with a wireless sensor node, the front-end device for acquiring data from various sensors. Data is sent to the cloud before being displayed to users via the dashboard. The front-end device presents significant challenges, particularly for clinical applications. In addition to collecting accurate bio-signal data, it must meet certain critical requirements such as portability, real-time monitoring, and power efficiency. The data transmission process consumes significant energy in the sensor node. As a result, reducing the number of data transmissions becomes critical to reduce power consumption. This paper focuses on the sensor node design tailored explicitly for biomedical applications and introduces an ECG data compression implementation. This study examines both the sensor node's performance and the compression algorithm. On the sensor node, a lossy compression technique known as K-RLE is used to reduce the number of transmissions. The reconstructed ECG data shows that the sensor node effectively preserves all significant ECG signal events up to K = 15.

1. Introduction

Internet of Things (IoT) applications rely heavily on wireless sensor nodes. These devices collect measured samples from sensors and transmit the data to gateways or local monitoring devices. The sampled data can then be stored on a cloud server, making them useful for additional analysis, such as behaviour prediction and trend analysis.

This technology has a wide-ranging impact, including the biomedical field [1, 2, 3]. It has significantly improved the sharing of information between medical professionals and patients. With the advent of remote health monitoring, patients' well-being can be assessed from a distance [4, 5, 6]. In addition, this technology has significantly enhanced safety monitoring and fostered independence in communities, especially among older people [7, 8].

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Despite their numerous benefits, one of the most significant challenges in designing sensor nodes is their limited battery operation lifetime, primarily caused by the high energy consumption during data transmission. For sensor nodes intended for long-term monitoring operations, this drawback is amplified. As a sensor node device's energy consumption increases, the battery must be replaced more frequently, affecting the patient's comfort.

Compressing the acquired data before transmission to reduce its size is one potential solution to the problem of power consumption during data transmission. The data can be decompressed upon reception to recover the original information. However, this introduces additional overhead to the wireless sensor node device to perform data compression. The most important factor is whether the energy savings realised during data transmission outweigh the energy consumed during compression [9].

This paper focuses on the K-RLE lossy data compression algorithm, which aims to compress data efficiently and achieve energy savings. The algorithm's performance in compressing ECG data is specifically evaluated.

Lossy data compression techniques can be distinguished from lossless techniques. During data reconstruction, the lossy compression method eliminates certain information, whereas the lossless compression method fully restores the compressed data to its original state.

Figure 1 depicts the ECG signal, which includes essential event characteristics such as the P wave, QRS complex, and T wave. However, redundant ECG data exists between heartbeats. By compressing these redundancies, the compression algorithm aims to reduce the transmission load on the sensor node [10, 11, 12].

The five ECG data compression algorithms presented in Table 1 were selected based on their application to ECG sensors and hardware implementation. Various design characteristics, such as sensor type, microcontroller, transmitter, and battery capacity, are considered while evaluating the performance of each algorithm. The essential performance metrics are the compression ratio (CR), percentage root mean squared differences (PRD), node lifetime, and transmission sampling rate.

As evident from Table 1 , authors frequently employ lossy, lossless, or hybrid techniques. Small-memory devices and low-performance microcontrollers frequently employ lossy compression techniques [13, 14]. As seen in [15] and [16], hybrid and lossless data compression techniques typically require larger memory and higher-performance microcontrollers.

Bluetooth is the most popular communication technology, while Wi-Fi is also an option for data transmission. After implementing compression algorithms, the authors report a 22% to 40% improvement in battery life. Lossy algorithms achieve greater compression ratios than their lossless counterparts, thus, enhancing battery life.

Compression ratio (CR) and percentage root mean squared differences (PRD) are standard metrics for evaluating the compression performance of an electrocardiogram (ECG). However, additional techniques are employed to evaluate the quality of reconstructed ECG data following lossy compression. Cross-correlation, uncertainty measurement, SNR versus CR graphs, and visual quality analysis are employed in studies [1, 16, 17]. Although lossy compression causes distortion in reconstructed data, it is generally acceptable if essential ECG features are preserved, such as R peak events and other wave features. This preservation can be ensured by evaluating the reconstructed data with the ECG detection algorithms of choice [18, 19, 20].

The structure of the paper is as follows: Section 2 explores existing ECG data compression algorithms. Section III describes the proposed K-RLE algorithm's design method for sensor node integration. Section IV discusses the experimental results. Finally, Section V summarizes the paper with some concluding remarks.

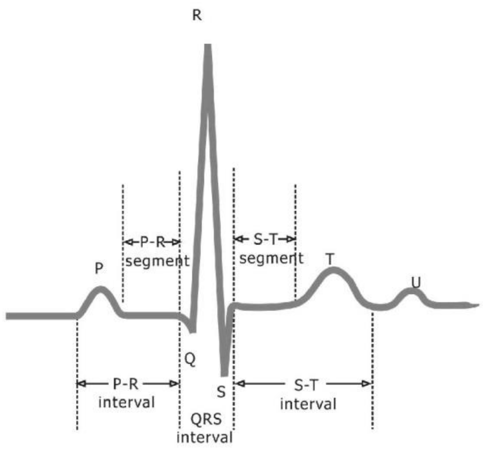

Figure 1: ECG signal with each interval labelled. Source: "e-Health Sensor Platform"

Table 1: ECG compression algorithm implementation in hardware trending from 2016 to 2020

Paper	[12]	[1]	[21]	[13]	[10]
Algorithm (Name/Type)	CS/Lossless	Enhanced DCT/lossy	Huffman/lossless	CS + BD/Hybrid	Noise filter,GBM &WTIT/lossy
Sensor	ECG	ECG	ECG	ECG	ECG
CR	2	5.1	2.53	5.4	9.4
PRD (%)	none	4.93	none	none	2.27
Microcontroller	TI C2530	SOC	Arduino Nano	Cortex M4	Arduino UNO
Transmitter	Bluetooth	Bluetooth	none	BLE	Wi-Fi
Battery (mAh)	600	230	none	none	none
Percentage change of battery life (%) [(V2-V1)/V1]*100	22% (55 to 67H)	40% (100 to 140H)	none	40%	none
Sampling rate (Hz)	200	55Hz	none	500	none

2. Methodology

The K-RLE algorithm utilised in this study is a lossy and simple data compression technique. The K-RLE system operates as follows: The first data point is initially selected as the reference data. Each successive data point is then subtracted from the reference data. If the result of the subtraction falls within a predetermined threshold value, K, the reference data is copied to the next data point. This procedure is repeated until the difference between the reference and nth data points surpasses the threshold K. The nth value becomes the new reference data and the procedure is repeated until the end of the data stream.

Figure 2 depicts an illustration of the K-RLE compression algorithm. The first five ECG data samples are depicted in Figure 2(a): 213, 214, 207, and 300. Figure 2(b) depicts the intermediate data generated during K-RLE compression. Figure 2(c) depicts the results of applying K-RLE with a threshold value of 10 to the compressed data.

To further illustrate the process, let's use the reference value 213 from the first row as an example. Each data point in the second through fifth rows is then subtracted from the reference value. Figure 2(a) shows the subtraction results in green font. The results of this subtraction are then compared with the threshold value K. For data points 214, 207, and 217, the differences are less than or equal to 10, satisfying the criterion. As shown in Figure 2(b), the reference value (213) is therefore copied to the respective ECG data points.

However, the difference between data point 300 and the reference value is 87, which exceeds the threshold value K. As shown in Figure 2(b), this data point becomes the new reference value, and the value 300 is copied to the intermediate data.

Once the calculation of data differences is complete, the algorithm regroups the samples as depicted in Figure 2 (c). Since there are four repetitions of the value 213 in this figure, these data points are represented as "4213," and the value 300 is displayed separately.

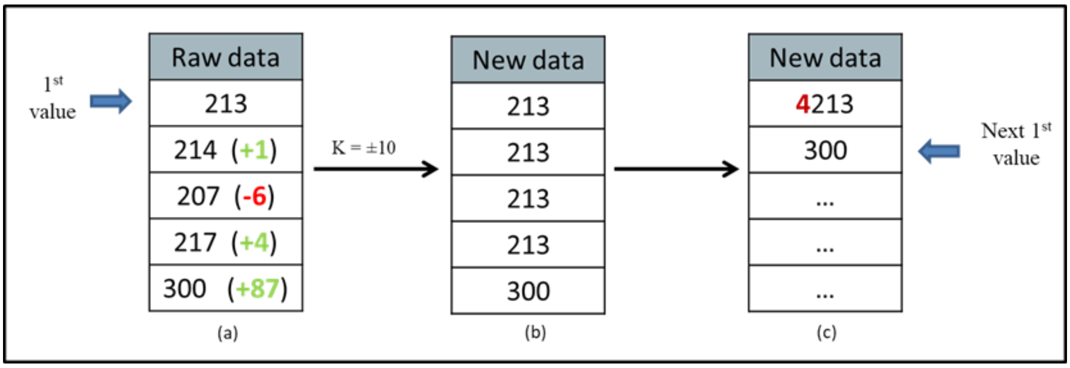

Figure 2: K-RLE data compression method: (a) raw data (b) intermediate data (c) compressed data

3. Results

Using Equations 2 and 3, respectively, the Compression Ratio (CR) and Percentage Root Mean Squared Differences (PRD) are calculated in this study. There are two sets of data samples, each employing a distinct K-variable ranging from K=5 to K=60.

$$\text{CR} = \frac{Input\ (raw) data\ file\ size}{Output\ (compressed) file\ data\ size} \tag{2}$$

$$\text{PRD} = 100 \times \sqrt{\frac{\sum_{n=1}^{N}(x[n]-\tilde{x}[n])^2}{\sum_{n=1}^{N}(x[n])^2}} \tag{3}$$

The average Compression Ratio (CR) and Percentage Root Mean Squared Differences (PRD) are displayed in Figure 3 as a function of the K-variable. Both CR and PRD are observed to increase with increasing K-values. This indicates that increasing the K-variable improves the performance of data compression but at the expense of an increase in data loss. At K = 5, for instance, the CR and PRD are 1.29 and 0.30, resulting in a compression ratio of 22.25%. At K = 60, however, the CR and PRD reach 4.32 and 6.39, respectively, with a maximum compression percentage of 76%. (see Table 2). Notably, when K equals 35, both compression performances are marginally superior to the preceding K-variable values, but they increase as K approaches 60. This increase is a result of greater differences between ECG plots, which distorts key ECG events such as the P-wave and T-wave.

The optimal compression rate is achieved at K = 10, where the CR and PRD are, respectively, 1.62 and 0.81. (see Table 2). Comparing the results of this study with those of five other studies as shown in Table 3, it has the lowest CR and PRD values and achieves the greatest improvement in battery life. These results indicate that the K-RLE algorithm can significantly improve battery life while maintaining low compression and distortion rates.

The Receiver Operating Characteristics (ROC) graph's area under the curve (AUC) is used to investigate the relationship between ECG wave detection and distortion of reconstructed ECG data. The rate of distortion (PRD) increases as K values rise. Two ECG samples yield an average AUC value, which is plotted in Figure 4.

Using the Multilevel Teager Energy Operator (MTEO) algorithm, Figure 4 summarises the average AUC for ECG wave detection performance against the K-value. A higher average AUC value, closer to 1, indicates highly accurate detection of ECG waves, whereas a value closer to 0 indicates less accuracy. The vertical axis represents the average AUC for each ECG wave, while the horizontal axis represents K-values ranging from K = 0 to K = 60. The colour of the line plot distinguishes each ECG wave. When K = 0, the graph represents the result of the original ECG wave.

The results indicate that the R wave has the highest detection performance on the original ECG sample, with an average AUC of 0.96, followed by the Q, S, T, and P waves. The detection performance of R and S waves remains constant as the K-value increases. However, the performance of Q wave detection degrades after K = 15, whereas T wave detection fluctuates when K reaches 15. At K = 20, P wave detection begins to decrease. As K increases, the Q wave deteriorates the most, followed by the T and P waves.

In conclusion, the compression algorithm has a negligible effect on certain ECG signal characteristics, such as the R and S waves, as their detection performance remains relatively constant. As K increases during the compression algorithm, the Q wave is significantly impacted, followed by the T and P waves.

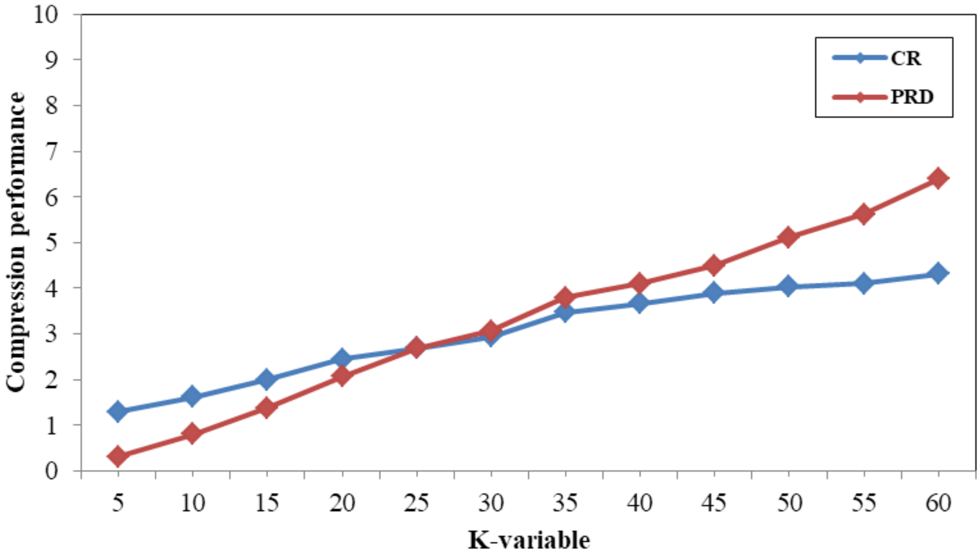

Figure 3: Graph of compression performance against K-variables

Table 2: Average CR, PRD and compression percentage based on the K-variables value

Performance / Value K	CR	PRD	% Compression
5	1.29	0.30	22.25
10	1.62	0.81	37.25
15	1.99	1.37	48.5
20	2.44	2.06	57.75
25	2.69	2.69	61.5
30	2.93	3.06	64.5
35	3.48	3.79	70.75
40	3.67	4.10	72
45	3.89	4.50	73.25
50	4.03	5.12	74
55	4.11	5.62	74.75
60	4.32	6.39	76

Table 3: Results comparison between literatures and this research

Paper	[12]	[1]	[16]	[13]	[10]	This Work
CR	2	5.1	2.53	5.4	9.4	1.62
PRD	None	4.93	None	None	None	0.81
Percentage changes of battery lifetime	22%	40%	None	40%	None	42.37%

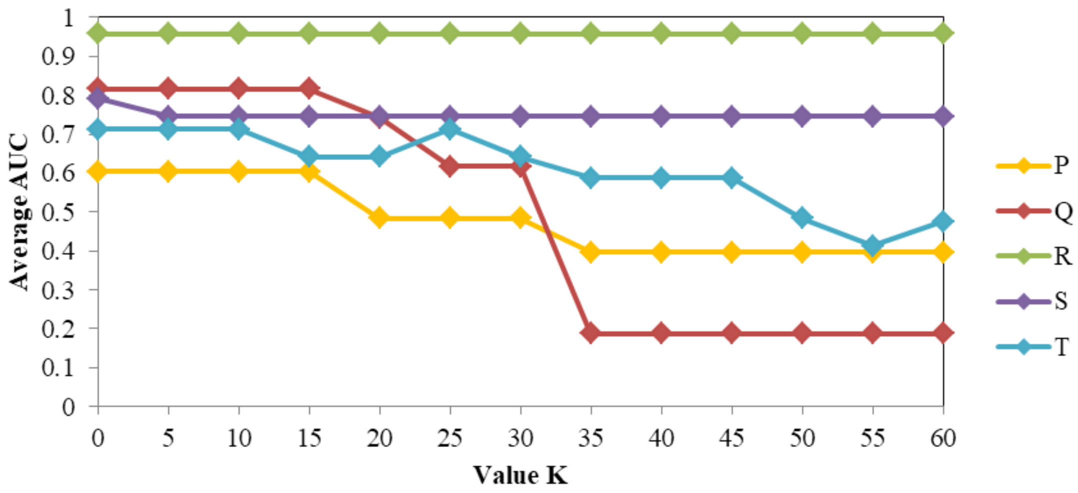

Figure 4: Graph of percentage battery level against time for LiPo battery discharging

4. Conclusions

The analysis in Section IV shows that when the sensor node reduces the number of transmission processes at K = 10, the sensor node achieves a significant 42.37 % reduction in energy consumption. In addition, this design produced a Compression Ratio (CR) of up to 4.32 and a Percentage Root Mean Squared Differences (PRD) of 6.39 %, indicating that 76% of the data can be compressed. To determine the optimal balance between CR and PRD while maintaining acceptable deformation of ECG main features, it has been determined that K = 15 yields optimal results. None of the waves have been completely deformed at this value of K, and the R and S waves remain unaltered until K = 60. This suggests that K = 15 strikes a suitable balance between data compression and preserving vital ECG wave characteristics.

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