Energy Saving on Constrained 12-Leads Real-Time ECG Monitoring

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***Abstract*—Continuous real-time electrocardiogram (ECG) monitoring can detect arrhythmia and provide early warning for heart attacks. Effective power management signals and controlling the mode of operation to reduce the need for full fidelity ECG signal. This work studies the impact of the base-delta compression technique for different cardiac conditions on power consummation. It also aims to evaluate operational strategies and their effect on the battery life when the ECG patch can switch between different operating modes (e.g., varying the number of leads according to the cardiac conditions). We use a binary classifier to inform the decision of switching between different operational strategies. Both scenarios are evaluated in terms of execution time, Bluetooth Low Energy (BLE) communication airtime, power consumption, and energy-saving ratios on a Texas Instruments CC2650 Micro-controller Unit (MCU). We compare the performance of the base-delta compression and changing the mode of operation scenarios on various cardiac abnormalities. Performance evaluation shows that operational strategies outperforms data compression in power saving for normal ECG readings by a double fold. In contrast, operational strategies incurs an additional overhead of 1011 ms during an abnormal status. However, base-delta satisfies the embedded platform constraints on execution time and airtime with 25 ms and 20 ms, respectively in the MCU environment.**

I. Introduction

The Internet of Things (IoT) has contributed significantly to the expansion of healthcare systems during the last decade [25] [4]. The wide range of medical sensors, especially ECG sensors, prompts the need for portable wearable monitoring devices, such as Holter monitors and cardiac events recorders. Holter monitors facilitate continuous cardiac events monitoring 24 hours, consuming a large amount of power to operate in constrained environments. Therefore, energy saving is critical in maintaining the sustainability of real-time ECG platforms. The proposed efforts to date, introduce several ways to optimize power consumption during the data acquisition and transmission phases. For example, data size reduction is commonly used in ECG real-time monitoring [27] to reduce the communication overhead required to transfer data between both ends. Changing operational strategies using Machine Learning (ML) and neural networks classifiers is another approach to reduce power consumption and support real-time ECG monitoring [11].

Nevertheless, all proposed efforts focus on power consumption optimization by implementing customized hardware circuits [8] or deploying classification on the cloud [7] [19]. As a result, there is a significant gap in testing the performance and durability of the ECG monitoring platforms on real ECG systems. Furthermore, the transmission time of captured ECG data and power-saving analysis on the constrained embedded environments are under investigated.

Optimizing energy consumption impacts the durability of ECG monitoring systems. If we reduce the computational power and the overall transmission time to send ECG readings over BLE, we can guarantee seamless continuous monitoring without interruptions due to battery depletion or power outage. Thus, this research aims to highlight three cornerstone facts on the road map of optimizing the power consumption of constrained 12-leads ECG real-time platform,

1) How do we minimize the consumed energy by an ECG patch in the constrained MCU environment?
2) What are the optimum approaches to achieve maximum energy saving with minimum processing and transmission time?
3) What is the effect of combining data reduction and switching the mode of operation on the total consumed power by an ECG patch?

The heart of the current research is to highlight the convenient approach used in the MCU environment from preserving power, minimizing the delay and computational time points of view. Three different approaches followed in this context; using the compression scenario solely compared to switching the ECG patch mode of operation solely as well as a merging of both techniques.We execute base-delta compression as a lightweight lossless technique on the MIT-BIH dataset for several normal and abnormal conditions. We compare the original state and compression output in terms of the total execution time, airtime over BLE, and the amount of saved energy after compression. Furthermore, logistic regression (LR) is deployed to classify normal and abnormal ECG signals. Based on classification results, the ECG patch mode of operation could be alternated between 1 and 12 leads which extends the operational time of the ECG patch. Moreover, we combine both base-delta and LR to compress the ECG readings after changing the mode of operation.

The main contributions of this study can be summarized as follows:

- Evaluate both power-saving and transmission time over BLE for normal and abnormal ECG signals after changing the ECG patch mode of operation due to the binary classification output.
- Highlight the difference between compression and changing the ECG patch mode of operations impact on energy saving concerning the total overhead on the MCU environment.

The remainder of this paper is organized as follows: Section 2 outlines previous research on energy demand optimization in IoT systems and ML/DL approaches for saving power in ECG monitoring systems. Section 3 describes the energy-saving methods on our constrained 12 leads ECG platform. A use case study is presented with the constrained requirements in Section 4.The experimental setup is explained in Section 5 concerning dataset characteristics, and power-saving scenarios using base-delta and changing the ECG patch's mode of operation using linear regression. Section 6 shows the performance evaluation of the proposed power saving methodology in terms of execution time, airtime over BLE, and power-saving ratios. Lastly, Section 7 provides concluding remarks and draws future directions.

II. Background and Related Work

The recent decade has witnessed an increased demand for portable real-time ECG monitoring systems [26] [10] [33]. Efficient ECG monitoring platforms are concerned with data acquisition techniques, compression transmission approaches, models for accurate diagnosis, and energy-saving methods while defining the design specifications for real-time systems.

Optimizing energy consumption in health monitoring systems attracts significant contributions to support continuous physiological measurements. Accordingly, existing research efforts differentiate between the energy demand and supply concepts in order to manipulate energy saving on the continuous monitoring platforms [34].

1) *Energy Demand*: The rapid evolution in continuous monitoring platforms generates great interest in evaluating the total energy consumed by wearable sensors [23] [13], signal pre-processing circuit modules [29], memory modules [21], and wireless communication modules [12] [15].
2) *Energy Supply*: To accommodate the increase in energy demands, self-powered techniques are introduced to maintain a stable power supply during data acquisition, processing, and transmission phases. For instance, energy storage using flexible batteries and supercapacitors facilitates portable power sources for wearable systems [3] [1] [32]. Furthermore, the energy harvesting concept opens the door for renewable energy usage [17] and obtaining the required power from human thermal energy and body movements [5].

There are limited contributions in the literature that address the impact of real-time data acquisition, signal processing and data transmission on the power consumption of ECG monitoring devices. The majority of these contributions aim to minimize required computational power through reducing the data size and wireless transmission time.

Data size reduction is achieved by applying lossy or lossless compression algorithms on ECG signals [28]. Moon et al. investigate a way to balance data reduction and data fidelity on ECG data received from the BioSemi Active Two system devices using discrete cosine transform (DCT), discrete wavelet transform (DWT), and R-peak validation [20]. Similarly, Rebollo-Neira in [24] evaluates DWT as a simple lossy compression technique on the MIT-BIH dataset. However, DWT achieves a high compression ratio with negligible delay. In both contributions, the experimental work is not tested on a real ECG system or a constrained platform to evaluate the performance and energy-saving at low distortion recovery. Reducing transmission time through lossless compression is proposed by Tsai et al. in [30]. The authors propose three separate techniques: (1) an adaptive linear predictor that selects the best ECG readings to decrease the prediction error, (2) an improved context-adaptive Golomb-Rice code for data storage optimization, and (3) a fixed length packing format to decode data in real-time. The authors compare the linear predictor and the remaining lossless algorithms in terms of compression ratio, but the transmission time and power-saving analysis are missing on the embedded platform. Campobello et al. [24] introduce a simple lossless algorithm named RAKE to encode the binary representation of an ECG signal during the pre-processing phase. The RAKE algorithm achieves a compression ratio of 2.67% compared to 2.43% and 2.25% in Huffman and Dynamic Pack. However, RAKE produces a high latency equal to 500 ms as it operates on blocks of data which is too high to meet the real-time demands in constrained environments. In a few works, both lossy and lossless techniques are combined to create a hybrid approach. Deepu et al. demonstrate this hybrid encoding system to control the transmission mode and power consumption in IoT enabled wireless sensors [6]. Despite the resulting high energy saving ratios, the implementation complexity is dependent on the selected lossy and lossless schemes. Furthermore, the compressed data needs to be decompressed locally at the sensor node which demands more storage and causes additional delay.

ECG classification algorithms support making the appropriate decision of switching to lower data fidelity mode which reflects on energy-saving for real-time platforms. For instance, Kung et al. [14] recommend the Random Forest (RF) algorithm with 98.63% classification accuracy for energy saving in ECG systems. They compare RF and other QRS detection algorithms in terms of sampling rate and sensitivity. Nonetheless, their work lacks a practical performance evaluation on real-time monitoring systems. Multistage pruning CNN achieves 97% accuracy in low-power ECG classification and a 60.4% decrease in run-time complexity [16]. On the other hand, CNN requires high computational power that renders its deployment on low-powered edge nodes unrealistic for real-time applications. Wang et al. [31] introduce an energy-efficient scheme for wearable ECG monitoring that consists of two processes: adaptive compression and neural network. In adaptive compression, the authors combine lossy and lossless techniques and switch between both based on the classification results from a tree-structured neural network (TSNN). The scheme scored 98.4% in diagnosis accuracy and a 99.9% reduction in computational complexity which in turn reduces the power consumption. One of the drawbacks of this scheme is the overall latency due to the execution time of the two processes. Such a delay prevents effective real-time ECG diagnosis.

III. Energy Saving Methods on ECG Platform

This work aims to investigate diverse power-saving techniques to evaluate their impact on the overall battery life in normal and abnormal cardiac conditions.

First, we study ECG data compression as a power-saving technique in various ECG cases to reduce the data size and hence its airtime. Second, we apply a lightweight ML technique on the gateway device to control the ECG patch's mode of operation to stream either 1 or 12 leads to the backend, thus also reducing the amount of data sent over the communication interface and contributing to power saving.

A. Energy Saving Using ECG Data Compression

According to the work proposed by Ouda et al. [22], the base-delta encoding algorithm satisfies the embedded environment constraints of ECG real-time platforms. Base-delta compression achieves a trade-off between reasonable compression ratios, low execution times, and low power consumption. In this paper, we study the effect of base-delta as a lossless compression on ECG signals with various normal and abnormal heart conditions to reduce the required airtime for data transmission over BLE. We test the technique on the annotated MIT-BIH public ECG dataset. Theoretically, airtime reduction is the key factor in minimizing the total power consumption on MCU [22].

B. Energy Saving Using Varying Mode of Operation

In a constrained real-time monitoring platform, we need to balance between processing time of ECG classification and accuracy for abnormalities detection. Badr et al. [2] present an intensive comparison between distinct ML algorithms, such as Random Forests (RF), Support Vector Machine (SVM), Decision Trees (DT), Logistic Regression (LR), K-Nearest Neighbour (KNN) regarding accuracy and execution time for ECG anomaly detection. From their experimental results, LR satisfies our ECG platform requirements in terms of accurate diagnosis and minimum computational complexity with 93.60% accuracy and 0.857 sec processing time. The binary classification will act as an intelligent decision-maker to control the ECG patch's mode of operation based on the current ECG readings. By controlling the mode of operation on the ECG patch, we can reduce the number of required ECG leads and thus reduce the total energy consumption required for data transmission.

IV. Use Case Study

The ECG system we are studying in this paper has been proposed by Badr et al. [2]. The authors provide a real-time cardiac monitoring system using deep learning and data streaming techniques to classify ECG signals and notify emergency responders based on analysis. The system consists of five stages, 1) data acquisition using 12 leads ECG patch, 2) data transmission over BLE, 3) data storage and streaming using real-time data engines, 4) data processing and analytics using a range of ML/DL algorithms, and 5) decision-making stage to notify healthcare providers. In this work, the authors evaluate different energy-saving approaches on the ECG patch within the constraints of their embedded environment (i.e., the TI CC2650 microcontroller chip) to maximize the battery lifetime.

A. System Requirements

The ECG real-time platform runs the data acquisition task at a 500 sampling rate (i.e., capturing one sample every two milliseconds). The data collection process requires 1 ms to execute. Therefore, the allocated time for other tasks including data compression, data logging, and data transmission equals 1 ms. Nonetheless, the proposed system runs compression, logging, and transmission on batches of samples collected in one second, which means 500 ms is available for running these tasks. This setup puts a stringent time constraint on the system. Hence, all energy-saving scenarios. The compression process and the decision making for switching the mode of operation also need to be completed during this time interval. Otherwise, it will be interrupted by the data collection task which has the highest priority to maintain the system availability.

The ECG hardware depends on the TI CC2650 microcontroller chip as a multi-standard wireless low-powered board with a real-time operating system (RTOS). TI CC2650 has a scheduling API that prioritizes the required tasks separately, such as data collection, data logging, data compression, binary classification, and data transmission to execute the highest priority task. The tasks' priority ranking is configured at the initial setup of the scheduling API. In our proposed platform, data acquisition has the highest priority to facilitate continuous monitoring. The compression task takes the second rank then binary classification, data logging, and data transmission over the BLE channel.

The required tasks are arranged in this order to ensure continuous cardiac events monitoring and fulfill the platform objectives: (1) Reduce the consumed power by the ECG patch through a lightweight compression technique that reduces the acquired ECG data before transmitting it over BLE to the backend system. (2) Control the ECG patch mode of operation using lightweight binary classification which acts as a smart decision-maker to optimize the energy consumption on the ECG acquisition hardware by switching to a lower number of leads when the heart conditions are normal.

V. Experimental Setup

Our experimental work will be explained in terms of training dataset, a power-saving scenario with compression, and a power-saving scenario with switching ECG patch mode of operations based on the binary classification output.

A. Dataset

To test both energy-saving strategies, we use the MIT-BIH dataset [9] which contains 48 ECG recordings for 47 patients. Each record contains 30 minutes of ECG readings collected at a 360 sampling rate. According to the work introduced in [12], the dataset includes 15 types of ECG arrhythmia. We work on the most common abnormalities, premature ventricular contraction (PVC), paced beat (PAB), right bundle branch block beat (RBB), left bundle branch block beat (LBB), atrial premature contraction (APC), ventricular flutter wave (VFW), and ventricular escape beat (VEB).

B. Power Saving Scenario with Compression

In this scenario, we apply base-delta compression on the MIT-BIH dataset and run it on TI CC2650 MCU. The annotated ECG recordings are pre-processed then forwarded to MCU for encoding and transmission over BLE to the cloud through the internet gateway, as shown in Figure 1.

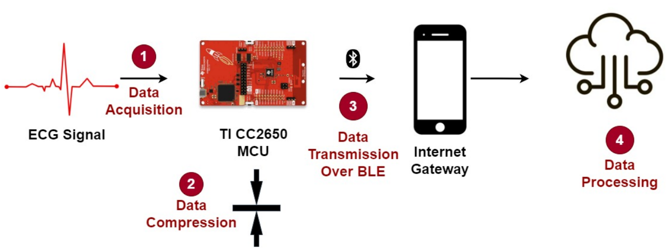

Fig. 1. Energy Saving Using Compression Scenario.

C. Power Saving with Varying Mode of Operation

In this scenario, we train a LR model offline using the annotated ECG recordings of the MIT-BIH dataset. The classifier then classifies the ECG readings acquired by the ECG patch into normal and abnormal classes. Based on the classification results, we manipulate the ECG patch mode of operation before transmitting the ECG readings over BLE as shown in Figure 2. The ECG patch runs the 12-leads streaming mode by default to enable full scale ECG analysis. Our proposed power saving approach is to let the ECG patch stream only single lead by default and switch to more leads when abnormal conditions are detected. Energy-saving would be feasible due to data size reduction between the 12 leads mode which generates 27648 bytes during 2 sec, and the single lead mode which generates 6144 bytes in 2 sec.

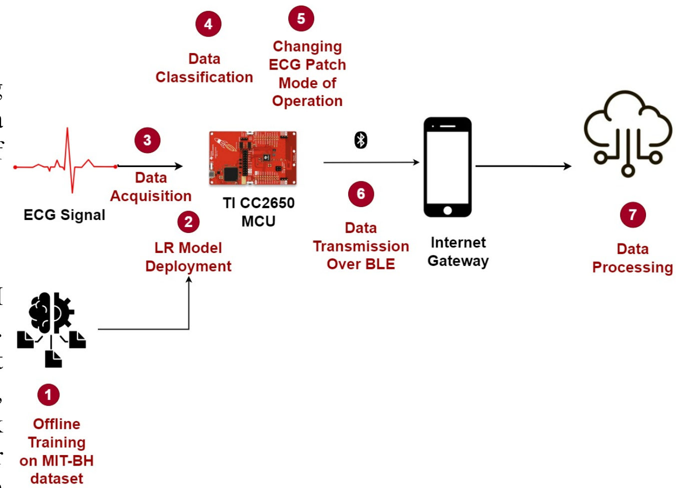

Fig. 2. Energy Saving Through Mode of Operations Manipulation.

VI. Results and Discussion

To maintain the ECG system availability, we must minimize the total power consumed in the acquisition and transmission stages. Energy-saving scenarios are assessed and compared with the baseline case (i.e., 12-leads row data without compression).

We evaluate each technique in terms of processing time, transmission airtime, power consumption, and energy saving. Based on the evaluation, we can decide which technique satisfies our system constraints on the execution time while saving more power. Table 1 shows the execution time after applying compression and binary classification scenarios under different ECG conditions. The results show that the compression scenario has the least overhead of all ECG conditions.

TABLE I
Execution Time (ms) in Compression and Classification Scenarios

ECG Signal	Compression Scenario	LR Scenario
Normal	25	857
PVC	25	857
PAB	25	857
RBB	25	857
LBB	25	857
APC	25	857
VFW	25	857
VEB	25	857

Table 2 compares the baseline, base-delta compression, and 1-lead ECG streaming scenarios in terms of the required airtime while transmitting the ECG data to the internet gateway over BLE with 2 MBPS physical layers and 251 bytes payload. The required duration to capture at least one full R-R signal equals 2 sec. As our ECG patch operates on a 500 sampling rate, we need 1000 samples to detect a complete cardiac cycle.

For the binary classification scenario, we consider the airtime in single lead mode for normal ECG. Next, we evaluate the airtime for 12 leads (8 channels) mode in the abnormal cases. As shown in Table 2, the normal ECG in compression and classification approaches has airtime less than the original state. In contrast, the compression approach has the maximum airtime in abnormal conditions.

TABLE II
AIRTIME (ms) BEFORE AND AFTER COMPRESSION AND CLASSIFICATION SCENARIOS

ECG Signal	Original Scenario	Compression Scenario	LR Scenario
Normal	45	18	34.2
PVC	45	21.6	154.2
PAB	45	21	154.2
RBB	45	21.3	154.2
LBB	45	21.9	154.2
APC	45	17.7	154.2
VFW	45	21.6	154.2
VEB	45	21.4	154.2

Table 3 compares the baseline scenario and the base-delta compression while transmitting ECG data for normal and abnormal status.

TABLE III
POWER CONSUMPTION (mJ) FOR SINGLE LEAD BEFORE AND AFTER COMPRESSION SCENARIO

ECG Signal	Original Scenario	Compression Scenario
Normal	500	293.8
PVC	500	333
PAB	500	326.4
RBB	500	330.6
LBB	500	336.8
APC	500	290.4
VFW	500	333
VEB	500	331.8

The comparability of power consumption after using the binary classification technique to control the patch mode of operation from 12 leads to a single lead highlights that the power consumption could be reduced in the normal condition only as shown in Table 4 with a 77.7% power saving. Consequently, we decided to compress ECG data resulting from classification and changing the patch mode of operation accordingly.

Table 5 summarizes the power-saving for the compression scenario on 12 leads and compression after in abnormal conditions. To obtain the power-saving readings, we calculate both the processing time and airtime for each ECG condition with respect to the base current of the TI CC2650 MCU [18] [22]. According to the results, applying base-delta compression after the LR classification has power-saving ratios close to the results of using compression only.

TABLE IV
POWER CONSUMPTION (mJ) FOR 12 LEADS BEFORE AND AFTER CLASSIFICATION SCENARIO

ECG Signal	Original Scenario	LR Scenario
Normal	1706	379.1
PVC	1706	1706
PAB	1706	1706
RBB	1706	1706
LBB	1706	1706
APC	1706	1706
VFW	1706	1706
VEB	1706	1706

TABLE V
ENERGY SAVING IN COMPRESSION AND CLASSIFICATION APPROACHES

ECG Signal	Compression Scenario	LR & Compression Scenario
Normal	41.2 %	33.5 %
PVC	33.4 %	30.9 %
PAB	34.7 %	31.2 %
RBB	33.8 %	36.8 %
LBB	32.6 %	31.3 %
APC	41.9 %	33 %
VFW	33.4 %	32.8 %
VEB	33.6 %	33 %

The experimental results conclude that despite the high power saving in normal ECG conditions, the processing overhead for both the compression and binary classification is high, rendering the system infeasible for real-time applications on MCU. However, applying the base-delta encoding on ECG data while on a reduced number of leads mode of operation enhances the power saving ratios in abnormal conditions. The compression technique turns out to be beneficial in power saving for all ECG conditions as it minimizes the airtime required for data transfer, while adding insignificant overhead.

VII. CONCLUSION

This study investigates distinct procedures to support continuous cardiac event monitoring within the constrained embedded environment of TI-CC2650 MCU. Both compression using base-delta encoding and switching the ECG patch mode of operation are evaluated with respect to the execution time, airtime over BLE, and energy-saving ratios. Changing the mode of operation approach exceeds base-delta in terms of energy saving of 77.7% for the normal conditions only when the mode of operation is changed from 12 leads to 1 lead. Nonetheless, base-delta encoding shows a stable power saving of 41.2% in normal ECG and 33% in abnormal status. Additionally, base-delta meets the embedded environment constraints with 25 ms execution time and 20 ms transmission time in comparison to 857 ms and 154 ms in the LR scenario. In the future, we plan to transfer the classification task to the mobile internet gateway where we can optimize the computational overhead and increase the power saving from both encoding and classification approaches.

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