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Optimization of low power consumption in wearable health monitoring devices and algorithm design

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Abstract. This paper surveys state-of-the-art approaches designed to decrease the power consumption of wearable health monitoring devices, thereby optimizing battery life. Specifically, this paper examines a concept proposed by researchers in a separate investigation, which involves active computation offloading. This entails developing an algorithm that efficiently distributes data processing tasks between wearable health monitoring devices and mobile applications. Researchers have successfully reduced system power consumption by up to 20% by intelligently offloading computations based on existing device characteristics. In contrast, another ECG remote monitoring system focuses on designing the lowest power sensor while keeping the system low cost and scalable. Lastly, this paper provides ideas to further lower power by state-of-the-art chip design, algorithmic and system design techniques.

Keywords: low power, wearable, health monitoring, ECG.

1. Introduction

Wearable health monitoring technologies have gained popularity as smartphones and electronic devices become an integral part of people's daily lives. These devices have wide applications, including mental stress detection, rehabilitation, and diet tracking. They hold the potential to offer more cost-effective healthcare solutions than traditional in-patient care. However, non-adherence to device usage remains a significant challenge that affects treatment outcomes. Battery life limitations further exacerbate this issue, necessitating the need for low power optimization strategies.

Most health monitoring devices share a common architecture comprising sensors, microcontrollers, and transceivers. In these devices, wireless data transmission and on-device computation for data processing are the primary power consumers. Technologies such as Bluetooth and airdrop are examples of wireless data transmission methods. Local computation incurs data processing overhead, as the on-device microcontroller often requires high power. Also, optimizing energy usage for wireless data transfer and on-device processing are often conflicting objectives, making the design of low-power wearable devices even more challenging.

The rest of the paper is organized as follows. In Section 2, the concept of computation offloading as proposed in [1,2] is examined and analyzed in detail. Historically battery technology advancement has lagged the growth of computation demand, thus computation offloading is likely a core concept of future low-power wearable devices. Section 3 evaluates an ECG (electrocardiogram) monitoring system which is the most common application of wearable health devices. In Section 4, various complimentary lower power design schemes are explored. The paper concludes with a summary in Section 5.

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2. Computation Offloading

Computation offloading is the concept of transferring data from an edge device to an aggregator for processing. The aggregator is a plugged-in device in the form of local server, cloud or other forms of computation platforms. Through offloading, the power consumption of the on-device microcontroller is minimized while the aggregator provides needed performance. In order to meet the real time requirement of wearable health devices, the decision for computation offloading must be dynamic taking into application requirements.

2.1. Classification Flow

Classification refers to the process of categorizing windows of biomedical signals into predefined feature sets such that decisions for offloading can be made. This process generally consists of four stages: acquisition, segmentation, extraction, and classification.

During acquisition, the on-device microcontroller collects data from sensors and stores it locally. The choice of sensor and data acquisition rate directly impacts the amount of generated data, thus significantly influences system power consumption. This data must be either processed locally, or transferred off device via Bluetooth or other wireless protocols.

In the segmentation stage, signals are divided into smaller windows and processed individually independent of each other. Segmentation is necessary because it may not be feasible to label a large dataset with a single feature. Sliding window and recursive approach are the two primary methods for segmentation. Recursive approaches aim to either partition or merge small segments of signals until a stop criterion is met, therefore exploring larger solution space. Sliding window approach however has the advantage of being straightforward and easier to implement.

Feature extraction is the next stage. Trade-offs must be made between accuracy and overall power consumption when deciding the number of features collected.

In the final classification stage, a trained classifier generates a class label for each window based on extracted features.

2.2. Dynamic Offloading

Once classification is complete, an energy model is used to dynamically determine whether it is more energy efficient to offload the computation or process it on-die for each window. This decision considers the overall accuracy requirement as a constraint.

The duty cycle of the system must also be included in the cost function. Transferring data off reduces the on-device computation but leads to longer time that the devices must stay on which costs leakage. In [3], the authors choose to keep heart rate and respiration rate processed on the node as the BT module consumes twice the power of the sensor board.

3. ECG Remote Monitoring System

The need for long-term care is on the rise due to the aging population, especially the baby boomer generation. As such, remote ECG monitoring devices that can be integrated within independent living communities and with large-scale IoT (Internet of Things) infrastructure are of high economic and health interest. In addition, the incremental cost to adding new patients to the system is an important cost factor to both the health providers and patients. In [4], a prototype of such an ECG remote monitoring system that meets above goals is described.

3.1. System Overview

The proposed IoT platform comprises three key pillars, which are

1) Sensors and actuator nodes (SANs)
2) Internet of Things server for management and visualization
3) User Interfaces

To achieve low power consumption, lightweight ECG sensors and other environmental sensors are utilized for real-time health data collection. Data transmission is achieved through wireless protocols such as ZigBee, Bluetooth, or WiFi. This is done with data being sent to a gateway that is connected to a home ADSL (Asymmetric Digital Subscriber Line) router.

The gateway manages regional sensor network protocols and packages sensor data for transmission to the IoT server. The message dispatcher facilitates communication between sensors and the IoT server, remaining agnostic to network protocols.

As an essential component, the IoT server defines a universal data format for handling heterogeneous sensor data. Standardized features within this format include objective identification, object type, measurement unit, geographic position, timestamp, and data field. This uniform format simplifies data processing and visualization by abstracting away unique communication protocols from data sources.

Lastly, the system features a user-friendly online interface accessible via various devices, including PCs, smartphones, tablets, and other internet-connected devices. This interface offers configuration options, data merging, and data processing capabilities for users and professionals, facilitating flexible data administration and analysis.

3.2. Sensor Design

Sensor design in a wearable system is often critical as it dominates other components in power consumption. The human activity recognition system in [5] is shown to have a sensing block that consumes more energy than the rest of the system combined. The wearable ECG sensor operates on battery power and is worn as a belt for painless, real-time ECG data measurement and transmission. The sensor's circuitry includes functions for ECG signal extraction, filtering, amplification, and digitization. The microcontroller receives and wirelessly transmits processed ECG data to the IoT server.

Designing a battery-powered ECG circuit is a challenging undertaking. Careful subsystem design is required to reduce size, cost, and power usage. Although some works fully incorporate and argue for integrated ECG AFEs, this study takes a different approach.

These researchers chose a system utilizing a general-purpose ADC (Analog Digital Converter) with an integrated digital filter in place of dedicated hardware. A high performance, high resolution, and low power ADC becomes the best option because the main goal is to decrease the system's power for a specific signal quality and non-recurring expenditures. The ADC is then preceded by a two-stage passive filter as the analog front end which is mounted using conductive rubber electrodes on a waist belt. A first-order high-pass filter with a rejection threshold of 0.05 to 0.1 Hz is used as the first stage. Any baseline wander that is still there can be dealt with through digital post-processing following analog to digital conversion. A linear high-pass filter with a 1Hz cutoff would be necessary to completely remove the baseline wander.

3.3. System Test

The proposed system is tested out in the real-world to evaluate its system performance, including its capacity to track ECG signals from several patients over a wide region and the data's accessibility. The test setup comprises six ECG nodes (sensor), an Internet of Things server, and a Zigbee gateway. Using an ADSL router, the ZigBee gateway connects the sensors to the server. A wide range of tests were conducted. This includes the ECG signal quality test which tries to determine the maximum operational range and data rate. The maximum data rate is determined by the number of ECG belts that may connect to a single gateway simultaneously. Finally, power usage is also tracked. These studies offered insightful information about the functionality and performance of their system, ensuring its suitability for long-term multi-patient ECG monitoring and data access via web interfaces.

In summary, this study assessed a different concept for wireless wearable ECG monitoring devices that is incorporated into an IoT platform and provides great ECG signal quality, long battery life, and multi patient monitoring in indoor environments. Their ECG sensor outperforms several front-end chip-based solutions in terms of energy efficiency. The entire sensor must be optimized, not just the front-end chip, for better sensor performance. The method, which makes use of easily accessible components, outperforms many systems that use specialized frontend chips. The cost-effectiveness of this system

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provides extremely effective administration, permits future work to improve health parameter monitoring, as well as enhances system reliability.

4. Other Low Power Techniques

Designing low-power microprocessors used in wearable medical devices is essential to lowering overall system power. There are several design principles that can be leveraged to achieve this goal.

4.1. Parallelism

Unlike a multicore CPU system where each CPU can execute heterogeneous instructions at any given time, the signal processing in medical devices is often SIMD (Single Instruction Multiple Data) style like GPU. This means a unified instruction cache, rather than dedicated instruction cache per core, can be sufficient for performance while drastically reducing memory access energy. This idea is explored in [6] and showed significant power benefits. An instruction crossbar (or I-Xbar) is included to provide flexibility of routing instructions to target processing cores.

4.2. Near-Threshold Computing

Since power is proportional to V^2, reducing operating voltage to near-threshold has a direct impact on energy consumption. This often comes at the cost of lowering operating frequency. However, performance can be gained back using parallelism or multi-core design as mentioned above.

4.3. Power Gating

It is possible the system performance is more than required at the lowest operating frequency and voltage, in which case the voltage cannot be lowered further to reduce energy. Instead, implementing power gating to shut down idle cores can conserve leakage and further extend battery life.

4.4. Design Point Selection

The total processor power is the sum of dynamic power and leakage power. Minimizing dynamic and leakage can be conflicting goals depending on the technology process node. Power gating adds to the complexity as it changes the dynamic vs leakage trade-off equation. One strategy to evaluate this trade-off is to conduct a sweep of F/V operating points in implementation and analyze the optimal point for an energy model.

4.5. Novel Computing Technologies

The rapid advances in deep-learning neural networks pose ever increasing challenges to low power computing. Novel, non-conventional computing technologies can be one of the answers. In [7], a mechanically coupled MEMS neural network is proposed for signal classification. It is a proof-of-concept design, but it demonstrated that certain nonlinearity attributes of the MEMS (Micro Electronic Mechanical Systems) system fit well with the requirements of neural network, and that makes MEMS a high potential direction for improving energy efficiency in wearable devices.

4.6. Power Management

Quality-of-Service (QoS) is of high importance to user experience for wearable medical devices. The need to charge or replace batteries is a significant hurdle to usage penetration. Harvestable energy (e.g., solar powered photo-voltage battery) is an effective way to alleviate the problem. In [8], the authors described various technologies to enable self-powered wearable devices. The design in [9] targets chronic respiratory diseases and uses harvested energy from thermal radiation and body motion. To maximize the potential of harvestable energy, paper [10] explores power management schemes to forecast or predict the amount of harvestable energy.

4.7. *Lossless Compression*

In a system that requires real time monitoring, transmitting the data can take a large percentage of the system power. Biomedical signals exhibit cyclic behaviour where there are periods of small fluctuation followed by large spikes in the signals. In [11], the authors proposed a lossless compression technique to take advantage of this observation. The core of the idea is to encode and transmit signal differentials. By adaptively adjusting the required bit precision, the system can dramatically reduce data transmission energy at the small cost of data compression overhead.

5. Conclusion

The design of a low power wearable health device requires a holistic approach spanning from system architecture, software, algorithm to microprocessor and sensor designs. This is an exciting and burgeoning field especially at the advent of the AI era. This paper surveys dynamic computation offloading and ECG monitoring system as two interesting design cases of a competitive wearable system. Both designs make conscious decision of partitioning real-time data acquisition from offline processing. To further reduce power consumption, various techniques from chip design to system design shall be considered, and this paper provides a brief introduction to several state-of-the-art design practices. Lastly, while low power is a key design metric, cost effectiveness and scalability also play an important role in commercial viability which can be achieved via careful system design.

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