Power Saving Techniques for Wearable Devices in Medical Applications

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IECON 2022 – 48th Annual Conference of the IEEE Industrial Electronics Society | 978-1-6654-8025-3/22/$31.00 ©2022 IEEE | DOI: 10.1109/IECON49645.2022.9968977

***Abstract*—Many people in the world are living with chronic diseases, demanding continuous monitoring, diagnosis, and treatment. Continuous physiological monitoring is key to providing preventive healthcare and accurate disease diagnosis, which leads to a growing demand for autonomous wearable technology. Wearable devices acquiring physiological information from the patient demand high-power efficiency to operate in a continuous acquisition mode. While power-saving techniques are applied in wearable devices for many application, very few are considered for biomedical applications. In this work, we explore existing techniques of power reduction for wearable medical devices. Our analysis addresses the power reduction of wearable medical devices and their generalization for different medical signal processing applications. In addition, we propose a taxonomy for power-saving techniques. The common categories of power-saving techniques are task scheduling, clock management, signal compression, and energy awareness. The presented analysis identifies the most appropriate and combined low-power techniques in wearable devices to reduce power consumption.**

***Index Terms*—Power Optimization, Power Saving Techniques, Continuous Monitoring, Medical applications, Wearable medical devices.**

I. Introduction

Nowadays, many people are living with complex health issues that adversely affect their day-to-day activities and overall quality of life. Moreover, there is an increase in the prevalence of chronic diseases as the age of patients increases [1]. Following chronic diseases, there are also increased complications in patients' illnesses, including hypertension and diabetes. Any delay in treatment and diagnosis of chronic disease leads to health degradation in the patient [2]. Therefore, it is crucial to detect the signs of chronic diseases at the initial stage. The monitoring, diagnosis, and prevention of chronic diseases can be done through continuous physiological monitoring. Continuous monitoring using wearable device technologies allows the earlier identification of signs of chronic diseases [3]. Regular measurements of physiological metrics is the primary purpose of wearable medical devices.

A wearable medical device can continuously acquire physiological information, helping physicians to be aware of the overall patient's well-being [4]. Moreover, a wearable device is not only limited to collecting vital signs of physiological parameters but is also capable of collecting signals from a patient's body and health-related activities [5].

Wearable medical devices can be worn or tied to a patient's body to monitor the patient's activities without limiting movement. Unlike other medical devices, wearable medical devices are suitable in healthcare environments due to their non-invasive and unobtrusive characteristics. Consequently, aged people can better benefit from using wearable medical devices to reduce their chronic disease deterioration rate through preventive healthcare.

Wearable devices promise continuous monitoring only when efficient power is provided. Consequently, it must require a minimum amount of power to operate. Considering that wearable devices are battery-powered devices, power management becomes essential in order to provide long-term and dedicated healthcare monitoring without power interruption. In fact, for many wearable devices, the battery lifetime is the fundamental problem. Therefore, the issue of low-power in wearable devices needs power-saving mechanisms to extend the run time and/or battery life.

Low-Power Techniques (LPTs) have been proposed in the past to optimize and extend the battery life for wearable devices [6]. LPTs are power reduction techniques that aim to minimize the power consumption of wearable devices [7]. Therefore, LPTs are becoming essential in wearable medical devices to monitor patient health status continuously.

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Many LPTs have been proposed specifically for wearable devices, but none is general enough for continuously monitoring patients. Furthermore, as wearable technology is quickly advancing, its power management remains challenging.The goal of our work is to propose a taxonomy for LPTs, and to identify the most promising LPTs for specific healthcare applications and the ones leading to the highest savings. The main contributions of this paper are mentioned below:

1) Presenting a taxonomy of LPTs in wearable medical healthcare applications.
2) Identifying the most promising LPTs for wearable medical devices.
3) Examining the challenges in applying LPTs in wearable devices.

The organization of the work is as follows. In Section II, the related works are discussed. Section III describes our novel taxonomy of LPTs in wearable devices. In Section IV, a discussion of the power consumption of wearable devices is provided. Finally, our conclusions are drawn in Section V.

II. Related Work

Low-power is an open and prolonged problem in wearable technology. In battery-operated wearable devices, energy-efficient is a key issue to reduce energy consumption for continuous patient monitoring in healthcare. In [8], energy-efficient human context recognition is applied to monitor a patient and its environment to infer ongoing tasks and living conditions. In wearable devices, energy-efficient is preferable for continuous monitoring while battery replacement is not appropriate. In hospitals, to offer continuous patient monitoring, the sensors need to collect data daily for healthcare [9]. Therefore, the work proposed energy-efficient for human context recognition applications in hospitals. Furthermore, it identifies personal context and environmental context recognition situations from the sensors. In their work, human context recognition recognizes and monitors the human environment like location and user activities such as walking, driving, and related, and improves personal context recognition. Their proposed solutions are the deactivation of power-hungry sensors, adaptive sampling rate, sensor set selection, and communications reduction. However, the work did not address the promising LPTs for human context recognition in wearable devices for healthcare [10].

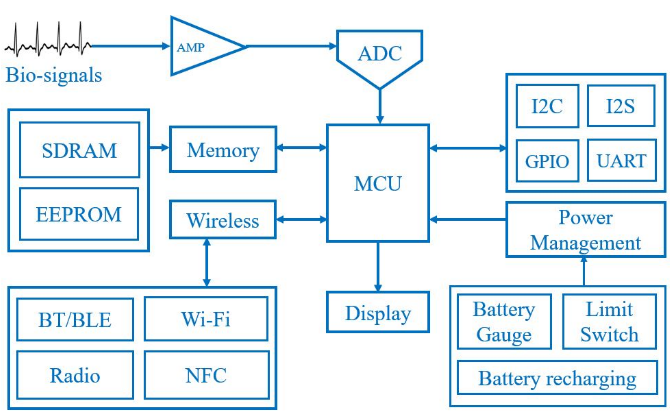

Fig. 1. Generic architecture of power management for wearable medical devices.

In healthcare, wearable devices have attracted a large interest [11] due to their reliable physiological measurements and continuous patient monitoring, which assist in reducing health risks. Moreover, they help physicians assess disease prevention and lifelong health quality [12]. The work in [11] focused on the three critical elements, namely sensors, batteries, and energy harvesting techniques. It analyses mechanical hardware devices, manufacturing, and energy harvesting techniques. In fact, the authors in [11] provide an overview of the applied techniques and their combination for further power savings.

The limited battery life remains the bottleneck for autonomous wearable devices. To overcome this constraint, some works lead to enhancing their energy efficiency [13]. The authors present energy-efficient solutions for diverse Internet of Wearable Things (IoWT) applications [12]. However, it is general and has no focus specifically on wearable medical devices. Additionally, the proposed solutions did not address the system-level power reduction of the wearables, and there are no details of power-saving techniques identified [14].

On the other hand, power saving is examined based on the sampling rate of biomedical signal processing in [15]. According to their work, to tackle the low-power in wearables, the authors proposed a decrease in the sampling rate due to its high impact on the power consumption [16]. However, their approach presents limitations since a high sampling rate represents a broad range of frequencies needed for some biomedical applications. Furthermore, the authors do not discuss the side effect of a low sampling rate on the quality of bio-signal processing. The low sample rate considers the power consumption side, but not the quality of signals.

The authors in [5] consider the low-power consumption as a key challenge for wearable devices. Their novelty is to address the communication security issues troubling the wearables in addition to the power consumption challenge. The authors intensively reviewed the existing literature and highlighted security threats to wearables under the categories of confidentiality, integrity, and availability. The work brings a significant demand on improving communication security and reducing power consumption of the wearable systems, which are fueling further research works in these areas [17]. The survey is general enough and focused on power efficiency, commercially available, and communication security issues of wearable devices. It provides detailed information related to wearable devices with workable solutions, but it addresses merely self-power wearable devices, which harvest energy from the environment. Unfortunately, it did not address other power reduction techniques of wearable devices.

Recently, many research works have been conducted to reduce power consumption. However, very few of them have LPTs as their primary goal. Many works target energy-harvesting techniques instead of power-saving techniques. In-

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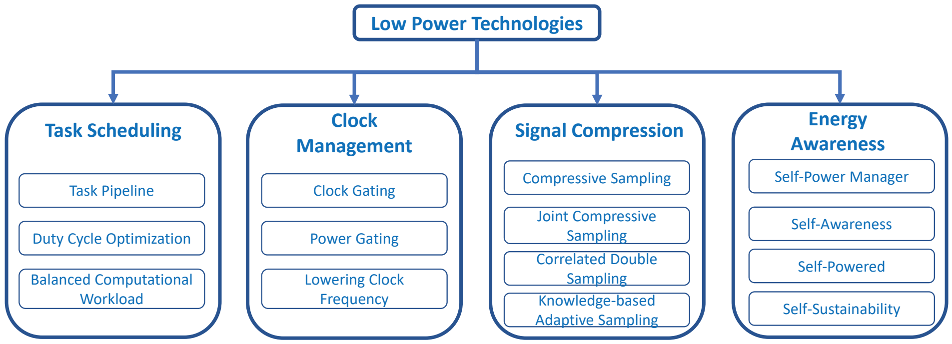

Fig. 2. Our proposed taxonomy. Several low-power techniques were identified and grouped into categories based on their common characteristics.

stead, we propose a taxonomy of LPTs based on their adoption in wearable medical devices. To our knowledge, no study has been conducted and is available in the literature on LPTs for wearable medical devices.

III. Proposed Taxonomy of Low-Power Techniques

As previously mentioned, low-power is the fundamental challenge for wearable devices. Power management is a top priority to extend the battery capacity for wearable devices. Fig. 1 depicts the common architecture that illustrates how is the power management of wearable devices. This architecture is the result of a comprehensive review of the architectures presented in the related literature. Based on the characteristics of this generic architecture, we can identify how LPTs affect to the components of wearable devices. As depicted in Fig. 1, these components can be grouped in processing, power management, Input/Output connectivity, wireless communication, storage capacity, and display categories. These components have a direct relationship with the power consumption of the wearable device. Therefore, LPTs can be applied to either the power management or to other components towards optimized power consumption.

To create our taxonomy, we have reviewed 1058 papers where LPTs are applied to different domains. Only the papers applying LPTs for wearable devices are considered in the first step. The papers that do not specify any type of medical applications and LPTs are excluded in a second step. Finally, only a set of 129 relevant papers targeted at wearable devices are utilized. From these collected papers, a set of LPTs is identified and categorized based on their common characteristics. The proposed taxonomy considers LPTs currently serving as power-saving methods. As depicted in Fig. 2, we identify four main LPTs categories such as: task scheduling, clock management, signal compression, and energy awareness.

A. *Task Scheduling*

Task scheduling plays a key role in extending the batteries lifetime. The tasks are run on the Central Processing Unit (CPU) for a certain amount of processing time. Once these tasks are completed, the CPU is idle. During this idle time, there is some amount of power consumed without performing tasks. However, task scheduling can adjust the lengths of this idle period by reordering tasks for their execution [18]. As depicted in Table I, task scheduling can be subdivided into subcategories based on the CPU workload and the scheduling of the tasks during execution time. In these techniques, the task scheduler controls the data on the channels and schedules based on priority. Based on its priority, the high-priority task gets the CPU as soon as it enters a ready-to-run mode, and then the low-priority task will enter running mode. Task scheduling categories enable the reduction of the energy consumption during idle time and to shut down of components of the architecture when there is no task ready for execution.

B. *Clock Management*

The techniques mentioned in this category are related to clock management. A considerable percentage of power is consumed during clock rates. Thus, this category dynamically and statistically controls the clock rates of the wearable systems [19], leading to significant energy savings in miniature devices [20]. As depicted in Table I, clock management contains subcategories of LPTs. The typical relation of these sub-categories is the adjustment of the period of the clock to reduce power consumption. Sub-categories of this type of LPTs manage the power consumption by applying a cut-off of the idle clock cycles, lowering the frequency, and turning on or off the clock for a specific group of flops.

C. *Signal Compression*

Acquisition and reconstruction of signals are essential in the signal processing of medical applications. Signal compression uses the advantage of sparse signals to reduce the samples needed to reconstruct the original signals significantly [21]. As depicted in Table I, signal compression can be subdivided in subcategories, which have common characteristics. These subcategories can be the compression of the signal to save storage capacity or to reduce the bandwidth consumption in the data transfer.

D. *Energy Awareness*

Energy awareness techniques are applied where replacing and/or recharging a battery is not possible, as for instance, when the patient is under critical health conditions [13]. These techniques inform the patient about the battery status before it

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TABLE I
SUMMARY OF THE PROPOSED TAXONOMY AND DESCRIPTION OF LPTS.

Categories	LPTs	Description
Task scheduling	Balanced computational workload	Reduce workloads and shut down physical machines, which become idle after tasks.
	Duty cycle optimization	Periodically placed the machine into sleep mode.
	Task pipeline	Parallel execution of multiple tasks.
Clock management	Clock gating	Cutting off the clock during the idle cycles of the flip-flop.
	Lowering clock frequency	Reducing clock speed and turning off the clock source of the peripherals.
	Power gating	Shutting off the current from unused blocks.
Signal compression	Compressive sampling	Reduce the computational complexity to reduce power consumption.
	Correlated double sampling	Reduce direct current offset and low-frequency noises.
	Joint compressive sampling	Recovery of large signals from the small subset of measurements.
	Knowledge-based adaptive sampling	Estimate the optimal sample frequency using adaptive sampling.
Energy awareness	Self-awareness	Train and automatically reduce power consumption.
	Self-power manager	Smart power technique that manages the power by setting parameters and policies.
	Self-powered	Harvest energy from external energy sources.
	Self-sustainability	Provides the sustainable power supply of the wearable device.

is under critical conditions. As depicted in Table I, energy awareness contains subcategories of LPTs. Sub-categories of this LPTs category are aware of the battery status to change the operational mode of the device. Unlike other LPTs categories, these subcategories help wearable devices to operate without replaceable batteries or external electronic power due to remote monitoring. Therefore, energy awareness sub-category techniques support wearable devices to be aware of the battery's lifetime.

IV. DISCUSSION

Our proposed taxonomy has categorized LPTs applied on wearable devices for medical signal processing applications, but it can be similarly discussed based on the type of medical application where the LPTs are applied. Most physiological signals like Electrocardiogram (ECG), Photoplethysmography (PPG), Electromyogram (EMG), Electroencephalography (EEG), Electrooculography (EOG), and Phonocardiography (PCG) are acquired using wearables are used to calculate heart rate, blood pressure, hypertension, and diabetes. Although most of the analyzed papers discuss LPTs for medical applications using ECG signals [22], [23] and PPG signals [24]–[26] in wearables, other papers focused on EMG signals [27], EEG signals [28], EOG signals [29], [30] and PCG signals [31], [32].

Most of the LPTs are applied on wearable systems acquiring ECG signals (38%) as depicted in Fig. 3. The distribution shows that LPTs for wearable systems in medical applications are distributed in 23% for PPG signals, 18% for EEG signals, 10% for EMG signals, 7% for EOG signals, and 4% for PCG signals.

As depicted in Fig. 4, most wearable systems utilize techniques that can be categorized in the signal compression category of our taxonomy. Task scheduling and clock management are also the other categories widely used in wearable systems.

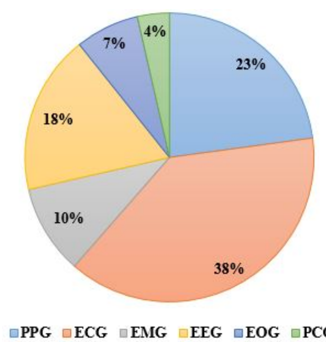

Fig. 3. Distribution of low-power techniques in wearable medical devices based on the target medical signals.

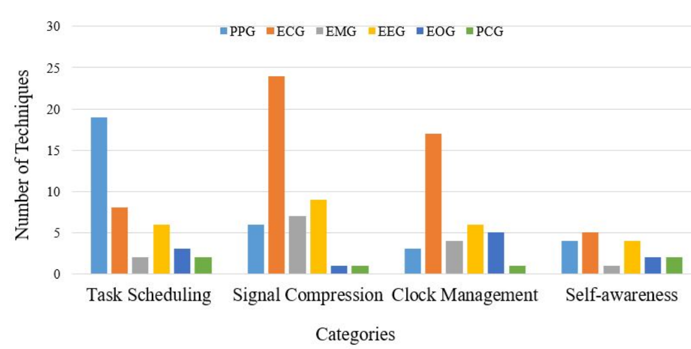

Fig. 4. Categorized power-saving techniques. The major categories of taxonomy power-saving techniques are based on their common characteristics in medical applications.

Notice that few wearable systems employ the self-awareness category to extend battery life.

A more detailed categorization is shown in Fig. 5, where it is possible to appreciate that the duty cycle optimization is commonly used to acquire PPG signals. Among them,

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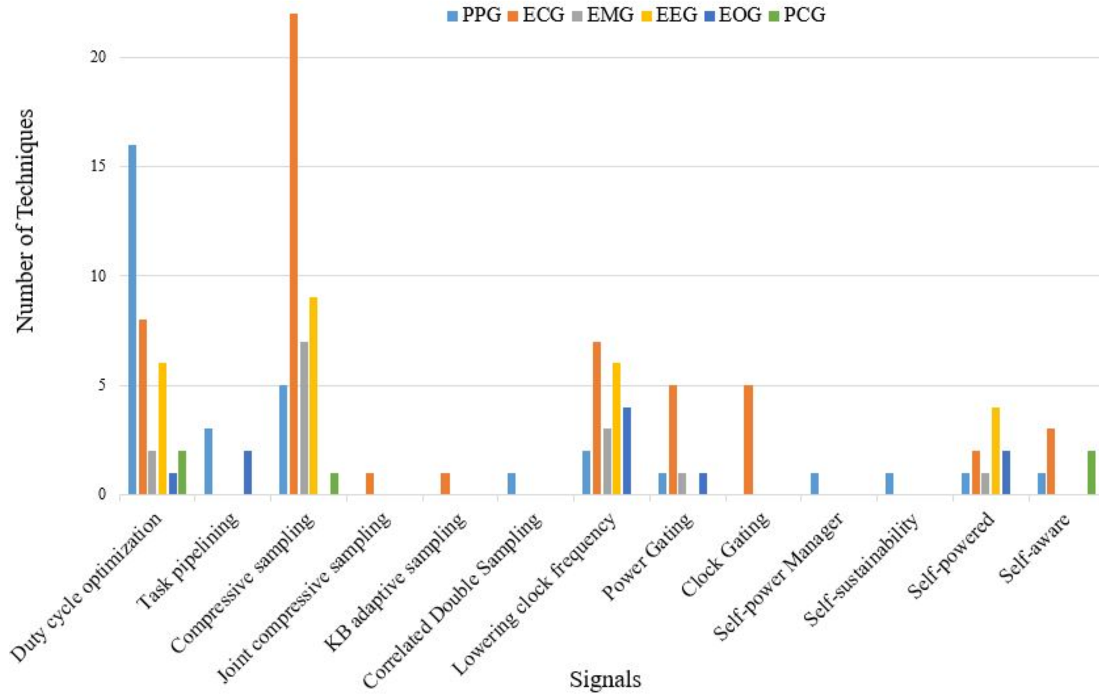

Fig. 5. Distribution of the low-power techniques based on the type of acquired signal. Identified power-saving techniques in wearable devices.

duty cycle adjustments [24]–[26], [33] are the most used. From the existing physiological signals, 59% of PPG signal acquisition applies the duty cycle technique. Because the duty cycle optimization controlled the rate of repetition of Light-Emitting Diode (LED) drive current. LED drive is one of the largest power consumers during PPG signal processing [33], [34], and [35]. For this purpose, duty cycle optimization turns on/off the LED drive light to control the repetition frequency between transmission and receiving time of signals.

Similarly, ECG apply compressive sampling to acquire signals through wearable systems. Accordingly, 40% of ECG signals, 32% of EEG signals, and 43% of EMG signals are applied compressive sampling. It is employed in a wide range of physiological signals, such as ECG, EEG, and EMG signals [36], and [37]. Similarly, around 40% of EOG signals apply lowering clock frequency, and 40% of PCG signals can be applied for the duty cycle.

On the contrary, we argue that clock gating, power gating, and knowledge-based adaptive sampling are not widely applied in PPG signals compared with ECG signals. On the other hand, compressive sampling is the most popular and widely applied technique to acquire ECG signals in wearable systems, as depicted in Fig. 5.

Some power reduction techniques are combined with other techniques. The analysis confirms that LPTs are combined [2], [39]–[41] to obtain the advantage of both techniques, as depicted in Table II. The low-power design requires a combination of several techniques at the design stage. The power optimization process excels when two or more techniques are effectively combined, leading to longer battery life. Numerous

TABLE II
SOME COMBINED LPTS FOR POWER OPTIMIZATION.

Ref	Year	Combination	Signals	Description
[38]	2021	Duty cycle optimization and compressive sampling	PPG	Sometimes the techniques are applied in multiple ways. For example, a duty cycle sometimes applies to the radio turning on/off. To overcome radio turns on/off limitation, compressive sampling is proposed because it exploits the sparse signals.
[22]	2017	Power gating and clock gating	ECG	Power gating and clock gating are techniques that reduce power consumption statically and dynamically, respectively.
[17]	2016	Self-powered and duty cycle optimization	PPG & ECG	Self-powered and duty cycle techniques harvest energy from the environment to reduce battery dependence. To conserve power consumption, the duty cycling optimization needs to be implemented by turning off the current when not in use.
[23]	2012	Compressed sampling and clock frequency	ECG	Compressed sampling can be applied to operate at a clock frequency to accomplish the task on time while lowering supply voltage to the minimum possible level.

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TABLE III
THE CHALLENGES IN APPLYING POWER-SAVING TECHNIQUES.

Techniques	Pros	Cons
Duty cycle optimization	Dynamically adjusted and optimum to apply the appropriate cycle. It is periodically placed into sleep mode.	It is not controlling the magnitude of the voltage but the duration of the high and low voltage values that resulting in the desired voltage level.
Compressive sampling	This technique helps to minimize the computational complexity and the sampling rate for sparse signals.	Most of the focus is given to the algorithmic perspective, while its real benefits in practical scenarios are still under-explored.
Clock gating	This technique reduces dynamic power dissipation by removing the clock signal when the circuit is not in use.	Unexpected clock edges can occur if the clock is enabled or disabled at the wrong time in the clock cycle.
Power Gating	Used to apply different circuital solutions that allow to switch off whole electronic systems or parts of them.	If all of the gates connected to the common power supply are placed close to each other and want to be turned off, the location and route present a challenge.
Clock frequency	The advantage of the clock frequency is that it helps to deal with different frequencies.	The selection of an inappropriate operating frequency of micro-controllers can lead to a significant percentage loss of battery power.
Balanced computational workload	Sharing services and maximizing the effectiveness of resources.	It is difficult to perform large-scale distributed architectures because it can cause significant fluctuations in service demand.
Self-awareness	The advantage of self-awareness is that it supports the wearable device in the decision-making of power saving.	Since it works remotely and sometimes it is exposed to security-related issues, processing, and storage limitations.
Self-power manager	It is a dynamic technique to handle power by setting its parameters and policies.	Sometimes it expects to develop its parameters and policies.
Self-sustainability	The self-sustainable wearable stores harvested energy.	It depends on the other sources of energy in the environment to be sustainable.
Self-Powered	It supports information processing technologies.	It operates by harvesting energy without external electronic power.
Task Pipeline	The task is divided into sub-tasks to perform the dedicated task.	There are no priority issues considered during executions.
Joint Compressive Sampling	It is used to combine different techniques and take advantage of these techniques.	The approach is only robust when it is combined with other techniques.
Correlated double sampling	Support reduces read noise by eliminating reset noise.	The amplifier noise is still present and is now the dominant source of the noise.
Knowledge-based adaptive sampling	Estimation of the optimal sample frequency using adaptive sampling.	It is rigid and focuses only on minimizing the energy consumption of hardware like sensors.

techniques can be applied in wearable systems to optimize power; for instance, when combining techniques are employed, the first technique turns on/off the current, and the second technique can reduce execution time.

As depicted in Table II, the most combined techniques are duty cycle optimization, compressed sampling, self-powered, self-sustainability, and task scheduling [17], [38], [42], and [43]. These combined techniques are widely applied to PPG and ECG signals for continuous patient monitoring. Finally, we argue that power state modes are widely employed as power-saving techniques [2], [39]–[41] in wearable devices.

One of the contributions of our work is to provide direction for the future application of LPTs for wearable devices as a guideline. Based on this, duty cycle optimization is a very efficient low-power technique when needed to control the LED drive. A balanced computational workload is an appropriate technique to execute tasks and then shut down physical machines. In the same way, the clock frequency plays a significant role in governing the power dissipation in wearables. So, it is an appropriate technique when need to make an adjustment, modification, or lowering clock rates. Clock gating is the appropriate technique to reduce clock power by shutting off the clock, which can be applied to reduce dynamic power dissipation, while power gating is applied to control static power dissipation. Similarly, power gating is a very efficient technique for saving power by turning off the power supply in inactive parts of the wearable devices. Similarly, compressive sampling is an appropriate technique when the sparseness of signal needs to be exploited to recover the signal from far fewer samples. A joint compressive sampling is required to jointly optimize power savings in wearables using various power reduction techniques.

Energy awareness is a LPT that needs to be applied when timely maintaining and recharging a battery is under challenging conditions. This technique informs the patients about the battery's state before it is under-critical. Self-power is a vital technique when needed to charge the battery from the environment, like solar, while a self-power manager is very efficient when it needs to develop its policy and parameters to optimize power. Knowledge-based adaptive sampling is an important technique to estimate the optimal sampling frequencies for sensors since the sensors may consume even more energy than the radio. A task pipeline is important to schedule tasks derived from multiple application flows on pipelines with an arbitrary number of stages. Self-sustainability is especially important when it is needed to store the charge for a prolonged time in harsh conditions. Correlated double sampling is a very efficient technique for measuring a known condition and an unknown condition while maintaining sensor-limited noise performance. Finally, the work presents the challenge of applying LPTs to wearable devices. As depicted in Table III, the pros and cons of applying LPTs to wearable devices are explained.

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V. Conclusion

This work presents a taxonomy for power-saving techniques intended to extend wearable medical devices' battery life. This proposed taxonomy facilitates the identification of the most suitable techniques based on the target application. Duty cycle is the most popular LPTs to acquire PPG and PCG signals for wearable systems, whereas compressive sampling for ECG, EMG, and EEG signals, and lowering clock frequency for EOG signals. Overall, we found that combining these techniques can potentially increase power savings for multiple medical applications.

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