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Article *in* Procedia Computer Science · January 2022

DOI: 10.1016/j.procs.2022.07.103

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Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 203 (2022) 693–698

Procedia Computer Science

www.elsevier.com/locate/procedia

International Workshop on Mobile4Medicine: Mobile Systems and Pervasive Computing for Personalized Medicine (M4Medicine)
August 9-11, 2022, Niagara Falls, Ontario, Canada

Facilitating privacy-preserving activity recognition in age-friendly environments through low-power devices

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Abstract

Advances in the Internet of Things (IoT) technologies are being applied in various industries, but lately, they are also finding applications in home-based healthcare systems. Such pervasive healthcare systems aim to enable older adults to receive better and more cost-effective care in their preferred home environment. Battery-powered IoT devices are essential for low-cost deployment, especially in rural areas. However, one of the main challenges for any battery-powered device is energy management so that the period between battery changes is prolonged. This paper proposes an energy-saving approach for a non-invasive passive infrared (PIR) sensor. The proposed method can put the device into a deep sleep to minimize the energy consumption and use hardware wake-up interrupts to make it functional again. The analyzed sensor kit allows the detection of persons, including recognition of their actions, while preserving the privacy of the person. This is very important for age-friendly environments where privacy-preserving is essential.

Keywords: Connected health; Internet of Things; battery consumption optimization; privacy-preserving devices

1. Introduction

There have been many advances in the Internet of Things (IoT) technology in recent years, causing an evolution in various industries. These advances have also propagated in the healthcare domain. New connected healthcare systems emerged with components that communicate remotely with one another [1]. Connected healthcare has the potential to improve the lives, health, and well-being, especially of older adults and people living in remote areas. Older adults often prefer to remain in their homes if they can live an independent life [2]. While specialized care is usually only available in dedicated medical facilities, the house may be equipped with ubiquitous devices that enable pervasive healthcare and well-being monitoring. Wearable IoT devices are used to detect activity and symptoms indicating med-

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10.1016/j.procs.2022.07.103

ical condition [3]. Non-invasive sensors could be used to infer the person's status with minimal interaction by the care receiver. Smart homes allow better support for the care receivers and reduce the cost associated with regular checks [4]. However, most proposed solutions assume that the connectivity is reliable and that there is an existing infrastructure to support such connectivity. Adapting existing homes with smart appliances and networked IoT sensor devices may increase costs, making solutions prohibitively expensive, especially in rural areas. A significant obstacle in enabling pervasive healthcare in remote and rural areas is the lack of network infrastructure [5]. In our prior research, a low energy (LoRa) network-based IoT architecture for rural healthcare was proposed [6]. The efficiency of non-invasive sensors can be affected by the positioning in the room [7]. Use of battery-operated IoT sensor modules was proposed to avoid additional costs from installing electrical connectivity to these devices. Audio fingerprinting techniques [8] and in general audio devices embedded in mobile devices [9] can be quite useful in activity and environment recognition so that in personalised medicine application the context of physical activities [10] and location is considered. Collecting such data, increase the processing requirements on the server (or cloud) side entailing the use of appropriate big data architectures for efficient and timely processing [11]. In turn, it requires the use of efficient algorithms for cluster-size and cost optimisation [12], as well as for scalable feature selection and dimensionality reduction [13].

Battery challenge and power consumption are common challenges for wearable and localization sensors used in various smart home and healthcare systems [4]. Aiming to save energy in IoT devices there have been proposed various approaches. One approach is to optimize sleep intervals of individual nodes in the wireless sensor network [14] considering the data variance. This approach increases the sleep time if the measured property is close to the mean value. A similar approach is based on the sleep/wake algorithm, and some authors claim to have achieved an extended battery life of up to 100 times [15]. Authors in [16] also propose an energy-efficient IoT architecture able to predict the sleep time of sensor nodes so it can save energy. Other approaches minimize the number of transmissions [17], perform data compression [18], or optimize wireless radio transmission parameters [19]. A zonal approach for data collection could optimize energy efficiency for collections of sensors [20]. Furthermore, there are already current legal requirements regarding the energy efficiency of sensors and IoT systems, especially for smart buildings. Authors in [21] give an overview of the legal requirements and the technologies present in the literature so that the smart systems are compliant with European regulations. Energy efficiency in IoT systems can also be treated as an optimization problem of selecting the right sensor and processing unit. In [22], authors review optimization approaches for energy efficiency of both sensors and processing units selection.

This paper describes an IoT device that combines five passive infrared (PIR) sensors into one module. This sensor module, when positioned above a person's bed, could help identify certain sleep disturbances [23, 24] in a non-invasive and privacy-preserving way. Furthermore, aiming to optimize the battery efficiency of the device, the power consumption using a high sample rate and high precision digital amp-meter was measured.

2. Materials and methods

Most of these approaches target the energy efficiency of the microcontroller, which commonly includes the wireless radio unit. However, depending on the application, a well designed IoT system might keep the microcontroller and the radio in a sleep or low power state for most of the time and rely on the sensor to wake up the device when some measured condition is reached. In this paper, the PIR sensor module shown in Figure 2 [23] is analyzed from the power consumption perspective. This device is used for non-invasive monitoring of persons in their homes, and in combination with additional sensors, it was presented that some sleep disorders could be detected by monitoring sleep [25, 26].

This IoT device consists of five HC-SR501 PIR sensors controlled by Heltec ESP32 WiFi Lora (V2) microcontroller. The microcontroller can communicate wireless via a WiFi network or the LoRa protocol. The connectivity is determined by the available infrastructure and by application-specific requirements. In the case of deployment in rural homes, LoRa is usually preferred. The PIR sensor is an off-the-shelf component, widely available and inexpensive, thus allowing this module to be manufactured cheaper even on a small scale. While fixed sensors could operate on energy from the electrical grid, this requires installation cost. The device reviewed in this paper gives the best results when installed on the ceiling [7]. Building codes, safety and aesthetics make it often not feasible to have a wired power setup.

Fig. 1. Five PIR sensor IoT device.

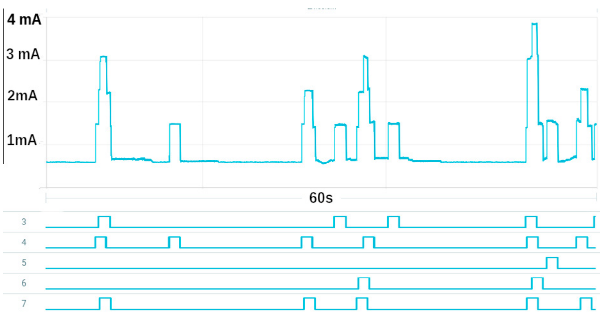

Fig. 2. Timeline for five HC-SR501 sensor when supplying 5V.

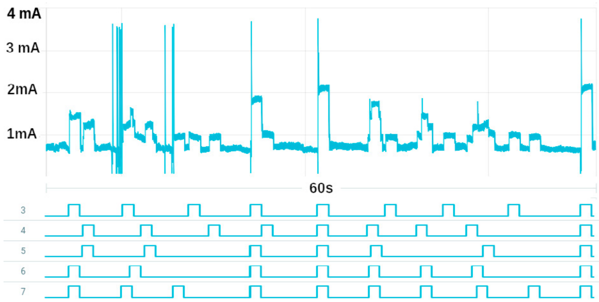

Fig. 3. Timeline for five HC-SR501 sensor when supplying 3.3V.

In the experimental setup, for measurements, a Nordic Semiconductor - Power Profiler Kit II (PPK2) is used [27]. This device acts as a precise amp-meter with logging capabilities and is connected to a computer via a USB interface. The sample rate used is 10000 samples per second. The PPK2 has an 8-bit digital input bus that sends a signal from the sensor or microcontroller to indicate up to 8 bits or 256 distinct status codes.

Table 1 presents the summary of the average current and power of the different components.

To simulate the entire IoT device, the type of the sensor used must be considered. To analyze the complete system, each sensor part of the IoT device should be evaluated. The off-the-shelf HC-SR501 PIR sensor's components work on 3.3V and use a linear voltage regulator (LVR) that uses heat dissipation to reduce the voltage and receive 5-20V input. The sensor has a jumper pin connected to the 3.3V line, which is used in the experiment, to supply 3.3V, directly bypassing the LVR.

When the sensor, powered on 5 V, detects motion, the output signal is raised too high, and the energy consumption is from 573 μA to 580 μA. It can be observed that the duration of the "On" state is constant, which is determined by the potentiometer on the sensor. To provide consistent results for all five sensors in the IoT device, the sensor module could be modified to include a fixed resistor. The duration of the "On" state should be set as low as possible, considering the limitations of the micro-controller. The current drawn by the sensor when the output pin is in the Off state, indicating no object is detected, but the sensor is actively looking to detect motion, is from 33 μA to 36 μA.

The current drawn by the sensor in the "Off" state is from 37 μA to 44 μA. While the current is higher, the energy consumption is lower due to the lower voltage supply. For the 3.3 V supply the average power consumption is 134 μW

Table 1. Power usage of individual components

Energy consuming device	State	Voltage	Avg. current	Power
HC-SR501 PIR sensor	Idle	5 V	0.035 mA	0.175 mW
HC-SR501 PIR sensor	Idle	3.3 V	0.041 mA	0.135 mW
HC-SR501 PIR sensor	Activated	5 V	0.577 mA	2.885 mW
HC-SR501 PIR sensor	Activated	3.3 V	0.170 mA	0.561 mW
Heltec ESP32 WiFi Lora (V2)	Active	3.10 V	38.35 mA	119 mW
Heltec ESP32 WiFi Lora (V2)	Sleep	3.24 V	3.07 mA	9.95 mW
Texas Instruments TPL5111	Idle	5 V	72 nA	360 nW

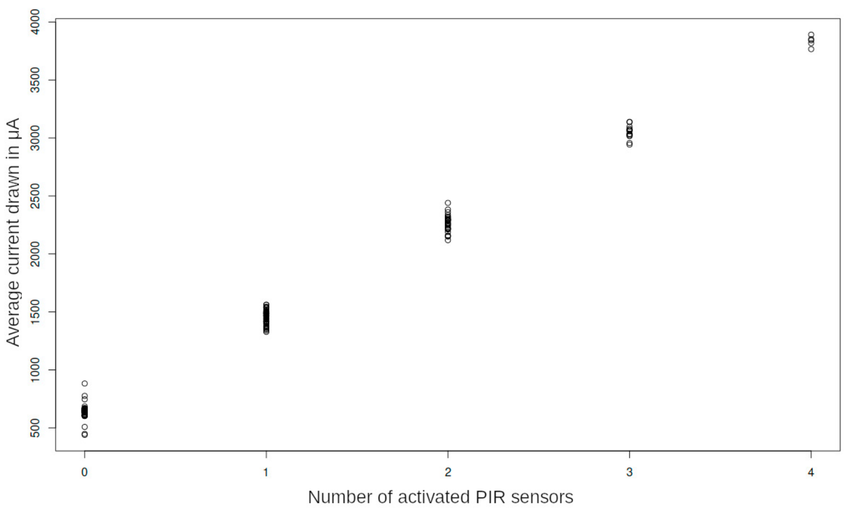

Fig. 4. Average current for 5 PIR sensors in relation to number of activated sensors (5V).

during the Off state and 562 µW in the On state. For 5 V supply the average power consumption is 176 µW during the Off state and 2885 µW in the On state.

As our IoT module includes five PIR , the energy consumption of all sensors when supplied by common 5 V and 3.3 V is measured. The power consumption is depicted in Fig. 2 and Fig. 3

3. Results and discussion

Figure 4 shows a scatter plot for the average current for five PIR sensors in relation to the number of activated sensors when 5 V power supply is used. When 3.3 V is supplied bypassing the voltage regulator, there is a higher standard deviation compared to the same measurement when 5 V power supply is used. Unexpected result of periodic activation of all five sensors simultaneously can be observed, which is not a result of detected motion. This effect could likely be reduced by improving the design of the circuit. Still, in this state, it limits the applicability of the off-the-shelf HC-SR501 sensor as a common 3.3 V switching supply is used to power the entire IoT device. However, due to the low current used by this sensor, the PIR sensors could be powered by a voltage of 5 V or higher based on the batteries used, or one sensor could be designated as a trigger and be connected directly to the battery supply.

Extending battery life often comes at a cost in performance and capabilities. Establishing an optimal approach depends on the specific characteristics of the hardware and the application-specific requirements. Another limiting factor is the cost.

Hardware improvements and using low power components is one optimization approach. Replacing linear voltage regulators (LVR) with switching DC-DC converters can increase efficiency in some cases. However, this is valid above a certain threshold, as a leak current of commodity DC-DC converters will make them inefficient. In the case of the components listed in Table 1 the microcontroller could benefit from using a DC-DC converter to reduce the power consumption; this applies for both the active and sleep states.

Using specialized low power devices like the Texas Instruments ultra-low-power timer TPL5111 [28], combined with low leakage switching components such as TPS22860 [29] the battery lifetime can be extended up to 80 times [30]. The downside is that measurements can't be conducted persistently but only when the TPL5111 timer wakes up the device. In the case of healthcare monitoring, external wake-up can be generated using a switch, pressure, or light sensors, depending on the application. In the case of the PIR sensor, the idle current is low enough that, in theory, a 2500 mA h AA batteries could power such a sensor in an idle state for several years. Therefore, one of the PIR sensors can always be powered on directly from the battery and be used to trigger the TPL5111 to enable the microcontroller to start collecting the data only when a person is in the room and will shut down itself when activity is not detected for a given duration.

Some applications require that each sensor activation be recorded and processed in the rural healthcare scenario. This is impossible if the microcontroller is off unless the sensor can store the readout value and send it upon request. The HC-SR501 sensors have a latching timer, and the active state can be kept long enough for the microcontroller to boot up and record the readouts.

4. Conclusion

IoT advances have the potential to improve pervasive monitoring of the health and well-being of people, especially for elderly persons living in remote areas with limited access to care providers. However, there are many challenges in deploying viable systems beyond the proof-of-concept phase. Due to positioning requirements and infrastructure limitations, battery-operated devices provide flexibility in installation and use.

This paper evaluated methods to reduce energy consumption and increase battery life in IoT devices. The analyzed sensor kit allows detection of persons, including recognition of their actions, while preserving the privacy of the person. In our experiment, a profile of five PIR sensor IoT devices was created. In the case of the microcontroller, it was concluded that a DC-DC switching converter should be used to power it using the 3.3 V input. In the case of the PIR sensors using multiple sensors connected to the same switching supply is less reliable, and the efficiency is low due to the low current. Furthermore, running the microcontroller consumes a hundred times more energy than the sensor, even in the sleep state. Thus, for this IoT device, we conclude that the optimal strategy is to use the PIR sensor as a trigger to an ultra-low-power timer to start the microcontroller only when a person is in the room or only when the sensor has detected the measured signal. While this approach does not apply to all the sensors and applications, it can be used as part of a more holistic system to optimize the longevity and usability of battery-powered healthcare IoT devices.

Acknowledgement

This work was partially financed by the Faculty of Computer Science and Engineering at the Ss.Cyril and Methodius University, Skopje, Macedonia. This article is based upon work from COST Action CA 19121 (Good Brother: Network on Privacy-Aware Audio- and Video-Based Applications for Active and Assisted Living) supported by COST (European Cooperation in Science and Technology). More information in https://www.cost.eu.

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