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Energy-efficient and Reliable Wearable Internet-of-Things through Fog-Assisted Dynamic Goal Management

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Abstract

Management of energy dissipation and battery life is a challenge in health monitoring wearables. Low-quality data collection, non-reliable monitoring process, and missing important health events are consequences of single-goal fixed-policy solutions. In this research, energy dissipation of IoT-based wearable systems is managed through a dynamic multi-goal approach. Health status of the user of a wearable device, the continuity of monitoring, and the accuracy of collected data are parameters we consider in our goal hierarchy to select a proper system management policy at run-time to achieve the most significant goal at a given time. In our approach, a dynamic observation process assesses the user and system data and a fog-assisted control engine detects the states, enforces the proper policy, and reconfigures the wearable sensor. To demonstrate our solution, we develop a real reconfigurable wireless sensor node with an ability to follow a set of parametrically defined policies and performed a set of experiments to find the most efficient setting. Our evaluation shows that the proposed system is able to reduce the power consumption by 44% and prevent the data loss due to battery shortage in 0.78% of total data collection time compared to a baseline system without a goal manager.

Keywords: Remote Patient Monitoring; Goal Management; Wearable Electronics; Internet of Things; Energy Efficiency; Fog Computing

1. Introduction

Chronic diseases are the main cause of death and disability in modern world [1]. They are described as persistent or long-lasting human health conditions like cardiovascular diseases, respiratory diseases, diabetes, and cancers [2]. Clinical data shows that the death risk of chronic patients increases rapidly when they face a sudden health deterioration [3, 4]. It has been shown also that the prevention of deterioration in chronic patients is possible and significantly reduces the mortality rate [5]. In most cases, the sudden deterioration starts via some early signs in patients' medical

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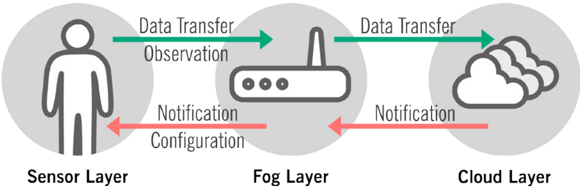

Fig. 1: The IoT-based architecture of remote patient monitoring

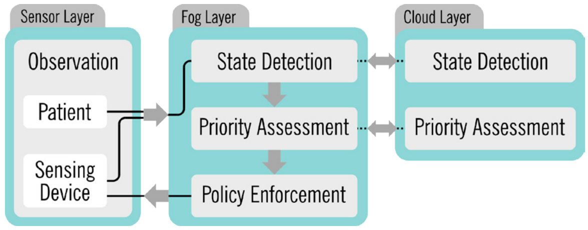

Fig. 2: The architecture of the proposed solution modules

parameters (e.g., heart rate, respiration rate, body temperature, blood Oxygen saturation, etc.) several hours earlier [6, 7, 8]. Finding those early warning signs via continuous patient monitoring provides an opportunity to reduce the risk of deterioration and make a potential death preventable [9].

There have been many efforts in hospitals on creating and implementing methods, tools, and devices for detecting and responding to the early signs of deterioration as soon as they appear [10]. However, the requirements for such methods are quite different in out-of-hospital settings. Out of the hospital, the patient is in fact the user of a monitoring device which is expected to be small, portable, and easy-to-use. Recently, the advancements in the Internet of Thing and wearable technologies have provided some solutions for in-home patient monitoring [11, 12, 13]. In such solutions, the patient uses a wearable battery-powered medical sensor which collects bio-signals and sends them to a local central device via short-range wireless communication. The local central device acts as a gateway and transmits collected data to a cloud server. The cloud server receives data from several patients, via several gateways and sensors. With a big amount of patients data available, the server-side processing algorithms are able to detect the signs of deterioration early enough to save the patients lives. (Figure 1)

In a remote patient monitoring, the continuity and permanence of the service are highly affected by the wearable sensor power consumption and battery size. Efficient deployment of sensors [14], utilizing sensors in their low-power and low-performance mode [15], reducing the coverage and the power consumption of wireless transmission module [16], and recording the signals periodically [17] are some of the power management methods the has been proposed to prolong the device work time. However, each one of those have some drawbacks. Reducing the number of sensors and using them in the low power mode, increases the ambiguity and reduces the signal quality. Reducing the radio transmission power increases the transmission delay and also the risk of disconnection. Periodic recording, instead of continuous data collection, increases the risk of losing some health status changes or deterioration early signs. A smart power management method would be able to use all such solutions together, each one as an individual goal to satisfy the requirements of a specific situation. To achieve a level of smartness, a system may benefit from self-awareness as a concept for considering its current state and current goal taking priorities into account. In our case, goals are high performance monitoring in abnormal conditions, long lasting monitoring, and accurate data collection and priorities are patient health status and lowest possible interruptions for battery replacement.

In this paper, we propose a multi-goal multi-policy IoT-based patient monitoring system using a self-aware power manager to fulfill the goals. The system observes the users health status, activity, and the current energy level of the sensor node, and according to the observations, prioritizes the defined goals. It then accordingly chooses an appropriate policy to meet the required goals. The system constantly observes the situation and dynamically updates the policy. To enable such an adaptivity, we develop a remotely reconfigurable sensor node to demonstrate our self-aware solution where we run a 24-hour continuous monitoring experiment.

The rest of this paper is organized as follows. In Section 2, we discuss the related works. Section 3 describes the goal management solution, the architecture of the system, and the development of the wireless sensor node. Section 4 presents the evaluation of the proposed system, and Section 5 concludes the paper.

2. Related works

In this section, we review recent efforts on developing wearable remote health monitoring systems and the related studies on self-awareness and goal management.

In the field of remote health monitoring, several devices have been developed to wirelessly record patient vital signs. Shimmer [18], ViSi Mobile [19], and VitalPatch [20] are the popular examples of ECG monitoring wearables available in the market. ViSi Mobile and HealthPatch are specifically designed for patients and have received CE and FDA approval. They continuously record and transmit data without any consideration for dynamic power management.

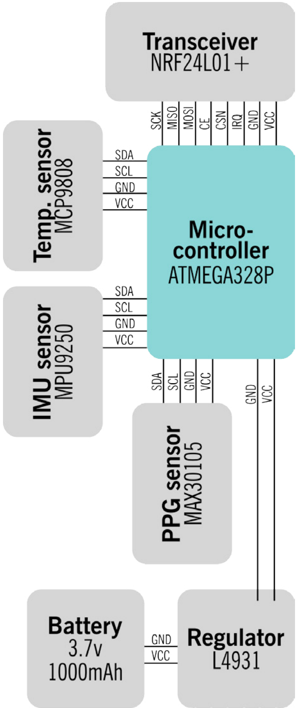

Fig. 3: Sensing device components schematic

Table 1: The state of components and the power consumption of sensing device working modes

Mode	Transceiver (NRF24L01+)	IMU (MPU9250)	PPG (MAX30105)	Microcontroller (ATMEGA328P)	Power Consumption (mW)
Sleep	Standby	Standby	Standby	Deep sleep	0.4
Observe	Standby	On	On: 6.2 mA	Normal mode	35.7
Normal	Sending	On	On: 6.2 mA	Normal mode	39.5
Low Power	Sending	On	On: 3.5 mA	Normal mode	38.9
Accurate	Sending	On	On: 12 mA	Normal mode	41.8
Send	Sending	Standby	Standby	Normal mode	20.2
Receive	Listening	Standby	Standby	Normal mode	95.1

Table 2: The details of system policies

Policy	Description	Notification	Recording	Sleeping
Policy 1	Emergency situation	To user, caregivers and hospital	Continuous	-
Policy 2	Power saving monitoring	To user	R minutes in Normal mode	2×S minutes in Sleep mode
Policy 3	Normal monitoring	-	R minutes in Normal mode	S minutes in Sleep mode
Policy 4	Accurate monitoring	-	R minutes in Accurate mode	S minutes in Sleep mode

Several solutions have been also proposed for the battery-powered sensor nodes in other IoT sectors. In the most recent solution proposed by Ye *et. al.*[21] the system autonomously decides its own operation mode based on reinforcement learning and in a decentralized way. Although their solution improves the sensor node power consumption, it can not update the goal function (i.e., the goal is fixed), and it does not consider the health condition and the availability of the energy source at runtime either. Guo *et. al.* [17] have developed a solution based on a continuous passive observation for critical event monitoring in wireless sensor networks. Even though their theoretical analysis and conducted simulations show a significant reduction in power consumption, their proposed method is solving a single fixed-goal problem.

Several research have been conducted on utilizing control loop models for implementing self-awareness in health monitoring systems. Azimi *et. al.* have optimized the sensor node energy consumption via ODA (Observe-Decide-Act) model [22] in [23] and propose an enhanced MAPE-K model [24] in [25]. Other self-awareness methods for health monitoring systems have been proposed in [26, 27, 13]. The state of the system, the patient condition, and a form of priorities have been considered in these works, but they have not considered the monitoring process as a multi-goal problem. Juntsch et. al. [28] have explained some example applications of goal management solutions in healthcare IoT, but they have not reported the implementation and efficiency of their solutions.

Goal management solutions have proposed also in the other non-medical research fields. Shamsa et. al. [29] developed a goal driven method for dynamic resource management in heterogeneous multi-core processors which led to a balanced result between low-power and high-performance policies. The key point of their method is a reward function in the controller which assigns a positive feedback for a successful priority assignment.

The novelty of our work is the proposition and demonstration of a self-aware model for optimizing a remote patient monitoring system considering the health status of the patient, the continuity of monitoring, and the accuracy of measurements as different goals of the system. We prioritize the system goals and develop a self-aware goal management algorithm that observes the user and system status in a control loop dynamically. The goal fulfillment approach in our proposed model is to trigger the data collection process only when major changes happen in the user and/or system status.

3. Proposed Method

To better understand the solution, it is first necessary to have an overview of our data collection method. We use three sensors in our sensor node to obtain the user's health condition, user's activity level, and system's battery status.

Table 3: A conventional Early Warning Scores (EWS) chart [31]

Score	3	2	1	0	1	2	3
Heart Rate (Beats per minute)	0-39	40-50	51-59	60-100	101-110	111-129	130+
Systolic Blood Pressure (mmHg)	0-69	70-80	81-100	101-149	150-169	170-179	180+
Respiration Rate (Breaths per minute)		0-8		9-14	15-20	21-29	30+
Body Temperature ($^{\circ}C$)		0-35		35.1-38		38.1-39.5	39.6+
Blood Oxygen Saturation	0-84	85-89	90-94	95-100			
Level of Consciousness				Alert	Reacting to voice	Reacting to pain	Un-responsive

The sensor node has an inertial measurement unit (IMU) to detect the user's activity, a photoplethysmograph (PPG) sensor to obtain vital signs, and a voltage sensor to estimate the sensing device battery level. The IMU sensor consists of a 3D accelerometer (showing the intensity of body movements) and a 3D gyroscope (showing the body posture). The PPG sensor consists of two light emitting diodes (LED) and one light sensor. LEDs illuminate the body skin and the light sensor measures the intensity of reflected light. The PPG signal shows the changes in the amount of Oxygenated blood in microvascular from which several vital signs including heart rate, respiration rate, and blood Oxygen saturation (SpO_2) can be extracted. According to the literature, the accuracy of the calculated vital signs is directly related to the amount of power used by the LEDs and indirectly related to user's activity. In other words, *the accuracy of calculated vital signs would be lower when a user has a higher level of activity necessitating more power consumption to enhance the accuracy.* The sensor node periodically records all the signals for a specific period of time and then goes to the sleep mode. It works based on a pool of policies allocate different quantity to the duration of recording time, the amount of power supplied for the PPG sensor, and the duration of sleep mode. More precisely, *the main objective of this system is to monitor the state of the patient and the system and select the most efficient monitoring policy for the sensing device to maximize the accuracy while minimizing the power consumption.* To include the battery replacement time in our experiments, we define a *power inaccessible period* term for those periods of time when the user is not able to replace the battery (e.g., when sleeping).

As shown in Figure 3, the sensing device consists of an ATMEGA328P microcontroller, an MPU9250 IMU sensor, a MAX30105 PPG sensor, and an NRF24L01+ wireless transceiver module. Each component of the sensing device has several power consumption profiles. The microcontroller can work in normal and deep sleep modes. The PPG sensor can work with one or two LED settings and the current consumption of each LED can be defined in a wide range from 0 to 50mA. The transceiver module can work in standby mode, sending mode, and listening mode with different radio signal strength settings. The microcontroller converts the analog battery voltage to digital values through the first analog input pin. To meet the requirements of our solution we defined 7 different working modes for the entire sensor node three of which are the different recording modes and the rest are sleep, observe, send, and receive modes. The sensor node works with 3.3v input voltage through a 3.7v Lithium Polymer battery and a regulator. We measure the power consumption of each working mode using a Power Monitor device. Table 1 shows the description of all working modes and the power consumption of each one.

The gateway device is an Onion Omega 2+ computer board coupled with an ATMEGA328P microcontroller and an NRF24L01+ wireless transceiver module. Onion Omega 2+ is a small yet powerful board with a 580Mhz MIPS processor and 128MB of RAM capable of running Linux OS, and is specifically designed for IoT applications.

The cloud server receives data samples and stores them for long-term health investigations. It also build a user behaviour model to find user sleeping time and calculate power inaccessible period parameter. Since the cloud server has Internet access it is capable of sending short messages or make automated phone calls through a web server when notifications are required.

The monitoring system consists of four modules: observation, state detection, priority assessment, and policy enforcement. As shown in Figure 2, we integrate the observation module in the sensor layer of our three-tier IoT architecture and the other three modules in the Fog [30] and Cloud layers in a distributed manner. The observation module checks the status of the user and sensing device frequently and in case of a major change sends a report to the state detection module in the Fog layer. State detection module calculates the health and activity state of the user according to the observation report and a history report from the cloud. It sends the calculation results to the priority assessment module. The priority assessment module considers the priority of system goals. Regarding the priority of parameters in the continuous monitoring, it also uses a history of the user's power inaccessible periods from the cloud layer. Policy enforcement module selects the next recording policy and sends it back to the sensor node.

3.1. Observation

The sensing device performs a periodic self-observation process every S seconds. In each iteration, it performs a simple assessment of the patient status by calculating the heart rate using a 10-second PPG signal sample and

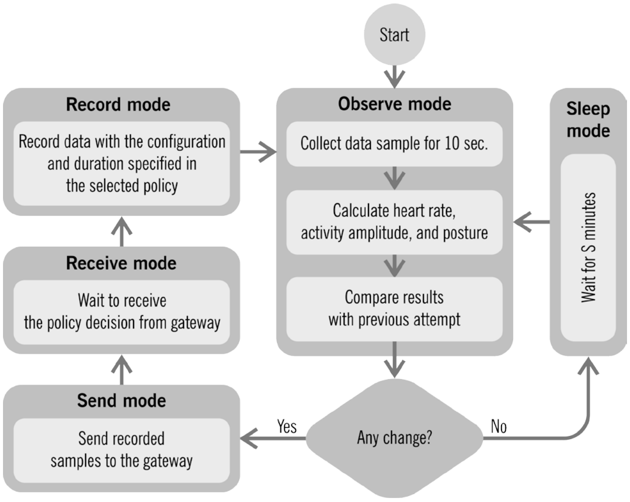

Fig. 4: Observation and recording flowchart in the sensing device

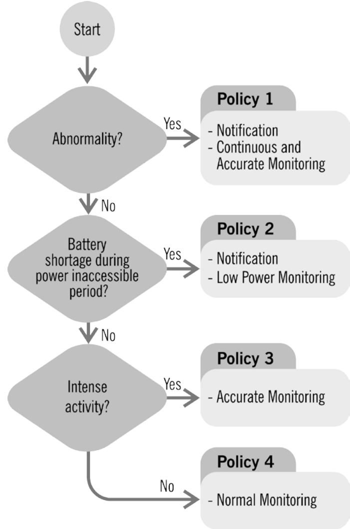

Fig. 5: Goals and priority assignment flowchart in the gateway

measuring acceleration and posture using IMU signal. The process compares the results with previous observation and if a major change is observed, it will send the recorded sample to the fog layer for further assessment and waits to receive the recording instruction. Otherwise, it goes to the deep sleep mode for S minutes and starts another loop after waking up. We mention here that technically, the ATMEAG328P cannot stay in deep sleep mode for more than 8 seconds, for this reason we enforce the S-minute deep sleep mode by repeating this 8-second period. The gap between these 8-second periods are very short (<1ms) and the change in the deep sleep mode power consumption is negligible. Figure 4 shows the details of the observation and recording flowchart.

To mark a major change in the heart rate, we use the standard healthy heart rate range extracted from the Early Warning Score (EWS) table [31]. EWS is a scoring method for tracking the health status of hospitalized patients. A reference table is used in this method (EWS table) which describes a standard range of each vital sign. Table 3 shows a conventional Early Warning Scores (EWS). According to this table, the heart rate considered as normal in the range of 60 to 100 beats per second. We mark a major change in heart rate if the heart rate value goes out of this limit or when it returns to the normal range. To mark a major change in the activity level, we consider five types of activity: sleeping, sitting, walking, jogging, and running. The sensor node distinguishes the sleeping and sitting mainly by user's posture, and detects the other activity types by using the amplitude of acceleration. Any difference between activity types in two consecutive observation will be marked as a major change.

3.2. State Detection

The state detection module in the fog layer receives the data samples from the sensing device and performs more advanced calculations which are not feasible to run by the sensor node low-power micro-controller. The gateway's wireless transceiver module is always in the listening mode waiting for a record sample from the sensing device. The gateway's side microcontroller receives data sample via transceiver module and sends it via serial communication to the Onion Omega 2+ computer board. The computer board filters the data and calculates the heart rate, respiration rate, and blood Oxygen saturation accurately. The received data also contains the sensor node's battery level and IMU signals. Similar to sensing device, the gateway classifies the user activity type and postures out of acceleration signal and the postures out gyroscope. The state detection module then sends a report to the priority assessment module. The report includes whether the user is in an abnormal health condition or not. It also reports the user's current activity and the sensor node's battery level. Since the blood Oxygen saturation is the most significant indicator of patient deterioration [32], we use the standard range of this parameter in the EWS table to find the user's abnormal health condition.

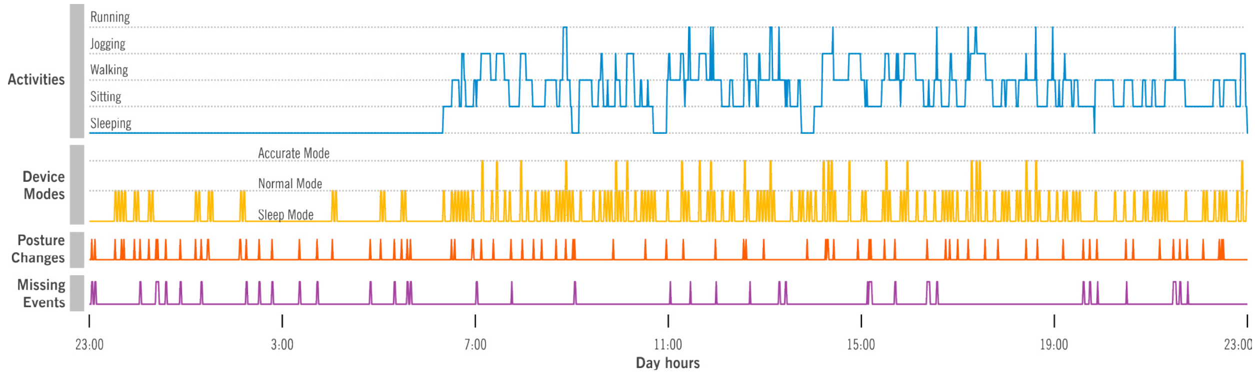

Fig. 6: A sample of generated activity and posture change pattern, sensing device states and missing events

3.3. Priority Assessment

This module receives the user and system states, and using a pre-defined priority hierarchy, selects the most efficient policy for the sensor node. In our monitoring solution, the highest priority is assigned to user's health status. If the state detection module reports an abnormality in the user's health condition, the system sends a notification to the user, caregivers, and hospital. In this situation, the system allocates all the available resources to continuous and accurate monitoring to provide remote healthcare professionals with a clear view of patient status before emergency service arrives. The next level of priority is assigned to case when *monitoring without interruption* is desirable. The main interruption in the system occurs due to battery replacement of the sensor node, and this should not happen when the user is not able to replace the battery (e.g., when he/she is sleeping), as this can cause some hours of monitoring interruption. In our system, the priority assessment module estimates the battery life according to current battery level, current policy, and a usual user's sleep time from the history of patient on the cloud server. If the battery failure is going to happen during the sleep time, it will notify the user to replace the battery before sleeping. The last priority in the goal hierarchy is assigned to the accuracy of the collected data. The sensor node should switch to a high power consumption mode to cope with the motion artifacts when a user is engaged with high intensity activities (e.g., running).

Figure 5 shows the goals and priority assignment flowchart. The gateway finds the patient abnormality status by checking the SpO_2 value in the standard EWS table range, and in case of detecting an abnormality, sends a notification to the cloud server where the server notifies the user/caregiver via a short message service (SMS) or a phone call. It also selects a continuous and accurate policy for the sensing device. If the user's health status is normal, it will check the current battery level as the next priority and requests the power inaccessible period parameter from the cloud server. If the battery is not enough to monitor the patient until the next morning, it will notify the user to change the battery before going to sleep. It selects a low power policy for the sensor node to minimize the monitoring interruption if the user does not change the battery. Finally, the gateway selects an accurate policy in case of intense activity to fulfill the last level goal in the hierarchy.

3.4. Policy Enforcement

Several policies are defined to describe the way sensing device works. The policy enforcement module receives the priorities and assigns a suitable configuration to the sensing device. Based on the sensor node's working mode and goal priorities, we define four different policies. Table 2 shows the details of each policy. After each data transfer from the sensor layer to the fog layer, the sensing device waits to receive recording instruction and the gateway device sends the configuration of each policy to it.

4. Evaluation

In the evaluation process of our proposed solution, we first present the method for finding the optimal settings for sensor node. Then we use the optimized setting to evaluate the performance of the system. As mentioned earlier, the configurable parameters of the sensor node are recording duration (R) and sensor sleep duration (S). We consider a range of changes from 1 to 10 minutes for each parameter. Therefore, we test the system in 100 different combinations

Table 4: Transition probability matrix for human activities

Activity Type	Sleeping	Sitting	Walking	Jogging	Running
Sleeping	0.95	0.01	0.04	0	0
Sitting	0.02	0.85	0.12	0.01	0
Walking	0	0.1	0.84	0.04	0.02
Jogging	0	0.01	0.22	0.76	0.01
Running	0	0.01	0.57	0.02	0.4

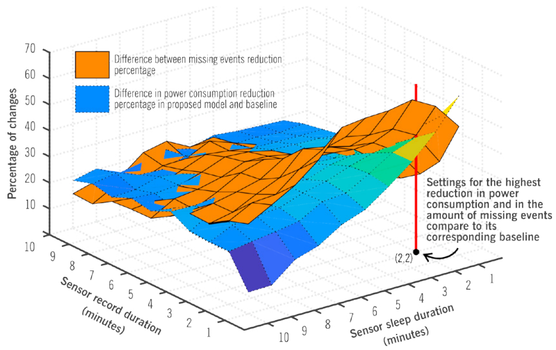

Fig. 7: The percentage of changes in power consumption and missing events comparing the proposed method and the baseline in different sleep duration and record duration settings.

of settings. As we look for the longest possible record and the latest priority that changes the state of the sensing device is the type of user's activity, we consider the user in healthy state and the battery to be fully charged.

A real examination of all possible settings needs diverse types of users, a very long duration of total records, and a large amount of history data. For this purpose, we generate the user's daily activities artificially utilizing the human daily activity pattern described in [33] and the probability of changes in human activities described in [34]. Table 4 shows the transition probability matrix (TPM) of human activities we derived out of [34]. Considering a random selection of 5 to 8 hours for user sleeping state, the TPM of human activities, and a set of randomized posture changes, we generate 300 days of daily activity patterns to test our solution. We run our algorithm on all 300 daily activity patterns using all 100 combinations of the configurations (totally 30000 tests) to find the best configuration for our setup. Our main goal is to reduce the overall power consumption of the sensor node. This goal is achievable by choosing the shortest duration for the record mode and the longest duration for the sleep mode, however a long sleep mode duration causes the system to lose some of the activity states or posture changes events. Therefore in each experiment, we measure also the total number of missed events during all sleep modes. Figure 6 shows the activity level, posture changes, the system states, and the missing events in one of the experiments. To evaluate the results of our test, we assume a specific baseline system for each configuration which uses a fixed recording and sleep duration without any management. Figure 7 shows the evaluation results in two intersecting surfaces. The blue surface shows the percentage of power consumption reduction in each setting compared to the corresponding baseline system. Similarly, the orange surface shows the percentage of missing events reduction. It shows that using 2 minutes duration both for recording and sleeping modes provides the highest power consumption reduction while keeping the number of missing events in the lowest value. In this state, the average power consumption of the sensor node is 11.16 mW which compared to the power consumption of the baseline system in this state (19.95 mW) is reduced by 44%. In the same way, the number of missing events reduced by 90%. With the selected setting, the sensor node can operate for around 62 hours using a single-use 230 mAh 3V CR2032 coin cell, and for around 13 days using a rechargeable 1000 mAh 3.7V Lithium-Polymer battery. Considering the power capacity of the CR2032 coin-cell we test the continuity of data collection true running the priority assessment algorithm on the 300 days activity sample data. It shows that the proposed priority assignment algorithm is able to prevent the interruption of data collection 15 times which prevents 56 hours of potential data loss equivalent to 0.78% of all collected data.

5. Conclusions

Risk of developing a chronic condition can be reduced by regular monitoring and observation of health condition. This, in turn, can help avoid sudden chronic attacks as well as improve the probability of early disease detection. A remote health monitoring system can be utilized for continuous health monitoring, but it needs to be optimized in terms of power consumption and data accuracy. In this paper, we defined these requirements as different goals of an efficient remote patient monitoring system. Then, a context-aware model to dynamically manage the fulfillment of these goals was proposed. The solution was demonstrated and evaluated through an IoT-based vital signs monitor. We optimized the system parameters and showed that using the proposed method, the energy consumption in the sensor layer can be reduced up to 44% in the optimized settings and data loss due to battery shortage can be prevented in

0.78% of total recording duration. In the future work, we will extend this study by considering other configurable factors that affects power consumption such as radio transmission range.

Acknowledgements

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References

[1] U. E. Bauer *et al*. Prevention of chronic disease in the 21st century: elimination of the leading preventable causes of premature death and disability in the usa. *The Lancet*, 384(9937):45–52, 2014.
[2] H. Wang *et al*. Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 19802015: a systematic analysis for the global burden of disease study 2015. *The Lancet*, 388(10053):1459–1544, 2016.
[3] M. M. Churpek *et al*. Association between intensive care unit transfer delay and hospital mortality: A multicenter investigation. *J Hosp Med.*, 11(11):757–762, 2016.
[4] S. Harris *et al*. Impact on mortality of prompt admission to critical care for deteriorating ward patients: an instrumental variable analysis using critical care bed strain. *Intensive Care Med.*, 2018.
[5] M. P. Young *et al*. Inpatient transfers to the intensive care unit: delays are associated with increased mortality and morbidity. *J Gen Intern Med.*, 18:77–83, 2003.
[6] I. D. Mapp *et al*. Prevention of unplanned intensive care unit admissions and hospital mortality by early warning systems. *Dimens Crit Care Nurs.*, 32(6), 2013.
[7] I. D. Mapp *et al*. Predicting clinical deterioration in the hospital: the impact of outcome selection. *Resuscitation*, 84(5), 2013.
[8] J. Ludikhuize *et al*. Identification of deteriorating patients on general wards; measurement of vital parameters and potential effectiveness of the modified early warning score. *J Crit Care.*, 27(4), 2012.
[9] M. Weenk *et al*. Continuous monitoring of vital signs using wearable devices on the general ward: Pilot study. *JMIR Mhealth Uhealth.*, 5(7), 2017.
[10] M. Brabrand et al. Risk scoring systems for adults admitted to the emergency department: a systematic review. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine*, 18:8, 2010.
[11] F. Firouzi *et al*. Internet-of-things and big data for smarter healthcare: from device to architecture, applications and analytics, 2018.
[12] A. Anzanpour *et al*. Context-aware early warning system for in-home healthcare using internet-of-things. In *HealthyIoT Conf.*, 2016.
[13] A. Anzanpour *et al*. Self-awareness in remote health monitoring systems using wearable electronics. In *DATE Conf.*, 2017.
[14] X. Liu. A deployment strategy for multiple types of requirements in wireless sensor networks. *IEEE Trans. Cybern.*, 45(10):23642376, 2015.
[15] D. Amiri *et al*. Edge-assisted sensor control in healthcare iot. In *IEEE GLOBECOM*, 2018.
[16] C. P. Chen *et al*. A hybrid memetic framework for coverage optimization in wireless sensor networks. *IEEE Trans. Cybern.*, 45(10):23092322, 2015.
[17] P. Guo *et al*. Sleep scheduling for critical event monitoring in wireless sensor networks. *IEEE Transactions on Parallel and Distributed Systems*, 23(2):345–352, 2012.
[18] Shimmer Sensing. *https://www.shimmersensing.com*, (accessed 19-12-2018).
[19] Sotera Wireless. *https://www.soterawireless.com/visi-mobile/*, (accessed 19-12-2018).
[20] Vital Connect. *https://vitalconnect.com/solutions/vitalpatch/*, (accessed 19-12-2018).
[21] D. Ye and M. Zhang. A self-adaptive sleep/wake-up scheduling approach for wireless sensor networks. *IEEE Transactions on Cybernetics*, 48(3):979–992, 2018.
[22] E. A. Lee. Cyber physical systems: Design challenges. In *ISORC*, pages 363–9, 2008.
[23] I. Azimi *et al*. Empowering healthcare iot systems with hierarchical edge-based deep learning. In *CHASE*, 2018.
[24] IBM Corporation. An architectural blueprint for autonomic computing. *White paper*, 2006.
[25] I. Azimi *et al*. Hich: Hierarchical fog-assisted computing architecture for healthcare iot. *ACM Transactions on Embedded Computing Systems*, 16(5), 2017.
[26] I. Azimi *et al*. Self-aware early warning score system for iot-based personalized healthcare. In *IoTCare*, 2016.
[27] M. Gotzinger *et al*. Enhancing the self-aware early warning score system through fuzzified data reliability assessment. In *MobiHealth*, 2017.
[28] A. Jantsch *et al*. Hierarchical dynamic goal management for iot systems. In *IEEE International Symposium on Quality Electronic Design*, 2018.
[29] E. Shamsa *et al*. Goal-driven autonomy for efficient on-chip resource management: Transforming objectives to goals. In *IEEE/ACM Design, Automation and Test in Europe Conference*, 2019.
[30] A. M. Rahmani *et al*. *Fog Computing in the Internet of Things - Intelligence at the Edge*. Springer, 2017.
[31] R. W. Urban *et al*. Modified early warning system as a predictor for hospital admissions and previous visits in emergency departments. *Advanced emergency nursing journal*, 37(4):281–289, 2015.
[32] J. P. Curry and C. R. Jungquist. A critical assessment of monitoring practices, patient deterioration, and alarm fatigue on inpatient wards: a review. *Patient Saf Surg.*, 8(29), 2014.
[33] M. Sani *et al*. Daily activity patterns of 2316 men and women from five countries differing in socioeconomic development. *Chronobiol Int.*, 32(5):650–6, 2015.
[34] A. Mannini *et al*. Machine learning methods for classifying human physical activity from on-body accelerometers. *Sensors*, 10(2):1154–75, 2010.