Self-Awareness in Remote Health Monitoring Systems using Wearable Electronics

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Abstract—In healthcare, effective monitoring of patients plays a key role in detecting health deterioration early enough. Many signs of deterioration exist as early as 24 hours prior having a serious impact on the health of a person. As hospitalization times have to be minimized, in-home or remote early warning systems can fill the gap by allowing in-home care while having the potentially problematic conditions and their signs under surveillance and control. This work presents a remote monitoring and diagnostic system that provides a holistic perspective of patients and their health conditions. We discuss how the concept of self-awareness can be used in various parts of the system such as information collection through wearable sensors, confidence assessment of the sensory data, the knowledge base of the patient's health situation, and automation of reasoning about the health situation. Our approach to self-awareness provides (i) situation awareness to consider the impact of variations such as sleeping, walking, running, and resting, (ii) system personalization by reflecting parameters such as age, body mass index, and gender, and (iii) the attention property of self-awareness to improve the energy efficiency and dependability of the system via adjusting the priorities of the sensory data collection. We evaluate the proposed method using a full system demonstration.

Keywords—Self-Awareness, Health Monitoring, Wearable Electronics, Situation-Awareness, Early Warning Score

I. INTRODUCTION

Vital signs reflect a patient's wellbeing status as well as the deterioration and amelioration of his or her condition. The monitored vital signs can also be the basis for predictions of a patient's health status. Research on cardiac arrests shows that certain symptoms can be observed long before the situation turns into a case of emergency; the advance apparition of symptoms can happen up to 24 hours before the actual health deterioration [1]. Early Warning Score (EWS) systems is a standard manual tool for predicting patients health deterioration which is periodically used by healthcare professionals to monitor patients' vital signs and interpret them to a level of criticality [2]. However, to support the recent trends in reducing hospitalization, there is growing demand for personalized and automated systems to enable in-home as well as mobile patient monitoring.

Internet of Things (IoT) and wearable technologies provide a competent and structured approach to improve the healthcare services in terms of social benefits and penetration as well as cost-efficiency [3], [4]. Due its ubiquitous computing nature, IoT-enabled wearables enable health monitoring systems such as EWS to continuously track and predict patients health status in an automated fashion [5], [6].

In [7], via a preliminary prototype, we presented how Internet of Things (IoT) and wearable technologies can be utilized to implement an automated EWS system. Our system deploys a wireless body area network (WBAN) – using a set of medical sensors attached to patient's body – to record physiological parameters and vital signs and send them to a cloud server for further processing and storage. Even though promising outcomes were observed, the system faced open issues which need to be addressed before it can be deployed in real field trials. Challenges such as situation-dependency, accuracy, and plausibility of input data, as well as constraints in sensor nodes call for more advanced optimization techniques to enhance the dependency of such systems. Several parameters affects the interpretation of vital signs outside the hospital (e.g., patient's activities, room temperature, barometric pressure) which need to be considered to reach a more realistic conclusion [8]. For instance, while a resting heart rate of 120 beats per minute would be an alarming sign for a patient, it can be completely normal while s(he) is exercising. Additionally, mobile and wearable sensors face disparate constraints such as energy efficiency, reliability, and computational power.

We believe self-awareness principles can be leveraged to reinforce the EWS system to tackle these open challenges. Self-awareness is defined as the ability of a system to be aware of its own state as well as the state of its surrounding environment to adapt to new situations [9]. The notion of self- and context-awareness can boost the EWS system to implement intelligent reasoning and decision making [10]. This can be realized by enhancing and personalizing the score calculation process to consider patient state parameters, to assess the confidence of the measured data and the corresponding decisions, and to optimize system-level characteristics by using the provided semantic information to adjust system knobs such as sampling and transmission rates and type of the required sensors in closed-loop manner.

In this paper, we propose a self-aware EWS system which provides personalization, self-organization, and autonomy for remote monitoring scenarios and offers intelligence in decision making process for patients in different situations. In addition, we leverage the properties of the self-awareness concept to improve the energy efficiency of the system and confidence of the calculated scores by adaptively adjusting the priorities in sensory data collection and processing w.r.t. environment changes and patient's emergency state. Moreover, we provide a proof of concept full EWS system implementation from development of cloud services to hardware-software demonstration of our prototype using a smart e-health gateway and a set of wearable and environmental sensors.

Score	3	2	1	0	1	2	3
Heart rate[1]	<40	40–51	51–60	60–100	100–110	110–129	>129
Systolic BP[2]	<70	70–81	81–101	101–149	149–169	169–179	>179
Breath rate[3]		<9		9–14	14–20	20–29	>29
SPO$_2$ (%)	<85	85–90	90–95	>95			
Body temp.[4]	<28	28–32	32–35	35–38		38–39.5	>39.5

[1]beats per minute, [2]mmHg, [3]breaths per minute, [4] °C

II. EARLY WARNING SCORE

Several physiological signs can be used for early warning of serious illnesses and deterioration (e.g., airway, breathing, circulation, etc.). These signs are always recorded but they are not constantly recognized, even though a structured record can make them "visible". To this end, early warning systems are developed based on the conclusion of several studies suggesting that there is often a delay in the response to the deterioration of a patient's condition [13]. However, the actual work of closely monitoring the patient and taking the appropriate action is dependent on the professional competence and as such is error prone as it is mostly manually done [14]. In addition, interpreting the individual signs into a single comprehensive status information about the patient is a difficult task. In the late 1990's, Morgan et al. [2] developed a scoring technique, Early Warning Scoring (EWS), which includes the core physiological signs. It aggregates a weighted score of six signs, respiratory rate, oxygen saturation, heart rate, systolic blood pressure, body temperature and neurological status. Each of these signs will have a value between 0 and 3 based on the actual reading, either high or low, and different level of action is required, including the level of expertise of the caregiver team, for each value of the EWS. Table I shows a sample of a simple EWS.

There have been some efforts to modify EWS systems (i.e., MEWS [15]) and or standardize it (i.e., SEWS [16]), in several countries such as UK , Ireland , New Zealand, and Sweden. However, all these efforts have been conducted in a non-automated (i.e., manual) fashion and only implemented in clinical environments.

III. SELF-AWARENESS

Self-awareness is a concept which can provide systems with necessary tools to obtain many dynamically changing characteristics of interest, such as reliability, adjustability and optimality. Many of these characteristics are of particular interest for the estimated 26 billion devices expected to be connected to the Internet of Things (IoT) by 2020[1]. Therefore, using self-awareness in various applications have been explored, including mobile applications [17], cloud computing [18], networks [19], and health monitoring system [20]. This has motivated us to explore various benefits that can be obtained through a self-aware design of a remote health monitoring system which uses wearable devices.

One of the prominent architectures for self-awareness is the Observe-Decide-Act (ODA) loop [21], [22], [23]. For current application also an ODA loop has been selected as the backbone of the system architecture. As shown in Figure 1, internal and external data are first collected through the sensor network and pre-processed (Observe). Next, the situation awareness and self-awareness core further assess and process these observations in order to choose the best configuration for the system (Decide). This configuration can be seen as two

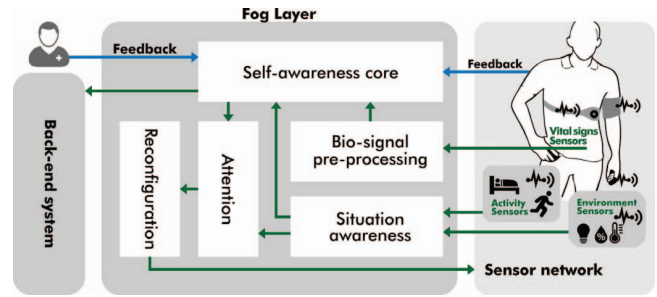[1]www.gartner.com/newsroom/id/2636073

Fig. 1.   Application of self-awareness concept to the remote health monitoring system

separate parts; first the part that helps the system to evaluate the health of the subject correctly, despite the potential noises or misleading values [5], [24]. Second, the part that tries to improve the system operations. Here, as shown in Figure 1, the main parameter under control is the "Attention", which is set based on the requirements (observations and decisions) of the self-aware units (Act). Attention, which determines various parameters related to the activity of the sensors (e.g., sampling rate, sleeping times, or precision), is then translated to the sensor network understandable commands in the "Configuration" unit and is passed to the sensor network.

It is important to note that a crucial part of the awareness of the system is its model of itself (and the environment). A designer can try to create as comprehensive a model as possible (which comes with the disadvantages of large resource requirement), and use complementary sensory data, nevertheless, it will not provide a full image until user feedback is provided to the system. This feedback plays an important role in improving the awareness and consequently performance of the system. This feedback can be provided by the subject using the remote device or the practitioner and the support system team. Each of these completes a certain part of the image, helping the system to create a better model of itself and its environment.

IV. PROPOSED SYSTEM ARCHITECTURE

In this section, we address the challenges from both the user and system perspectives by introducing a new architecture for local computing of out-of-hospital EWS systems. The architecture incorporates the foregoing self-awareness concept in an IoT-enabled health monitoring system. As illustrated in Figure 1, the main functionalities of smart gateways [25] in the Fog tier is divided into 5 different components, all of which are included in a closed-loop system to intelligently correct EWS values as well as adjust sensor network configurations regarding the self-awareness. According to the EWS implementation, these components are specified as follows.

A. Bio-signal Pre-processing

Bio-signal pre-processing unit receives raw signals from sensor nodes (i.e., heart rate, respiration rate, oxygen saturation, body temperature and blood pressure) and converts the data to a format usable by higher level processing units. The aforementioned preparation can be divided into two parts. First, pre-processing methods such as signal filtering and normalization are implemented in this component. Second, the signals are processed in order to extract the required medical information. For example, the heart rate data is extracted by detecting RR peaks in ECG signals. Finally, the component

Situation Awareness

Fig. 2. Situation awareness diagram

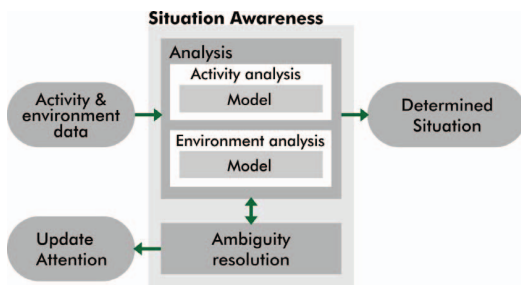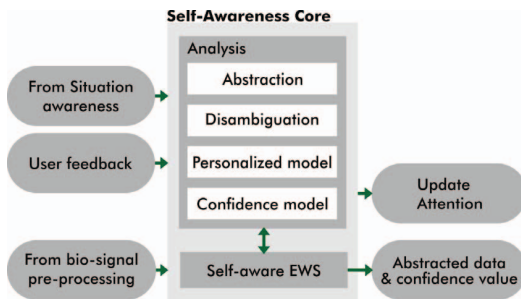**Self-Awareness Core**

Fig. 3. Self-awareness core diagram

transmits the filtered and extracted vital signs to the self-awareness core for further analysis and decision making.

B. Situation Awareness

Situation awareness is the component that receives activity and environmental data from the sensor network and provides patient situation for the core component as well as updating *Attention* in case of ambiguity in situation determination. As demonstrated in Figure 2, it includes two main units: Analysis and Ambiguity resolution.

Analysis unit includes activity and environment analysis units, each of which determines patient situation using a decision tree [26], however, several other approaches can be also utilized to determine the status of the patient activity and the surrounding environment [27]. In the activity analysis, patient's movements (i.e., acceleration in 3 dimensions) are classified in patient postures which are sleeping, resting, walking, jogging and running. Similarly, surrounding contexts (i.e., ambient temperature, ambient humidity and ambient light) are classified into different categories, for example as indoor/outdoor, day/night, etc.

Ambiguity resolution unit updates system's setup (i.e., Attention) w.r.t the determined situations. It requests new information sources (e.g., sensor node and database) in case of ambiguity in the Analysis unit results. For example, it sends a command to turn on the light sensor if the ambient temperature sensor is insufficient for determining the indoor/outdoor situation. On the other hand, to avoid unnecessary energy dissipation, this unit will request to remove a resource if redundancy is detected in situation determination.

C. Self-awareness Core

Self-awareness core is the main analytical component of the system which is in charge of tuning system configuration (e.g., energy and bandwidth) as well as refining abstracted patient data for the back-end users. This component receives vital signs and situation values and provides an enhanced

context-aware and personalized score which we call it Self-aware EWS. It also provides confidence assessment of the input data as well as correction methods to eliminate data inconsistencies. As illustrated in Figure 3, this component includes two main units: *Analysis* and *Self-aware EWS*.

Analysis unit consists of a semantic interpretation and models of activity and environment. The interpretation includes *Abstraction* and *Disambiguation* to provide meaningful information for the models and the back-end users. The Abstraction maps the medical data and the patient state to an interpretation. For instance, "low" is extracted as the emergency level for the patient with a heart rate of 140 per second while s(he) is running outdoor. Additionally, *Disambiguation* removes uncertainty in the abstracted values when the *Abstraction* encounters at least two conflicting values for the same condition.

The two data models are generated from pre-defined meta-data using rule-based and decision tree classifiers. The first model, "Personalized model", is defined according to the constant patient parameters such as age, body mass index (BMI), and gender. This model is updated during the patient monitoring process with user feedback, i.e., patients and health professionals. The second model is the "Confidence model" which is defined to indicate how confident the system is. The model considers three different aspects of medical parameters to calculate the confidence value: natural ranges of parameters (e.g., a heart rate beyond 220 heartbeats per minute is not acceptable), variation ranges (e.g., body temperature increases/decreases gradually), and dependency among events (e.g., high body temperature is relative to high heart rate) [24].

Self-aware EWS is in charge of adjusting the traditional EWS value for mitigating the susceptibility of the score to the patient and environmental conditions. Using the Analysis unit's results and the determined situation and a pre-defined rule-based algorithm, the Self-aware EWS unit calculates a new method by adjusting the boundary values shown in Table I [28].

Finally, the abstracted data (i.e., adjusted EWS and the patient's condition) along with confidence values and appropriate commands regarding the obtained results are transmitted to back-end system and the *Attention* component, respectively.

It is important to note that sending confidence value along with the score and other data, can lead to a significant enhancement of the system and patient's health assessment. For example, for the patient's health assessment, that is, if for any reason (such as missing or unreliable data), the system is not confident about its assessment, respective users are informed about this factor. For example, if the health of the user is assessed to be normal, however, the confidence level is low, the physician may choose to perform certain follow ups, e.g., calling the patient to ask some extra questions. Similarly, if the score is high but the confidence of assessment is low, it may be advisable to contact the patient for follow up controls rather than dispatching immediately the emergency team (which could be the case if both score and its confidence are high). Therefore, this parameter can be significantly helpful in avoiding misinterpretations.

D. Attention

Attention is the planning component which adaptively tunes monitoring knobs to enhance system characteristics as well as the confidence and quality of the sensory data. It receives
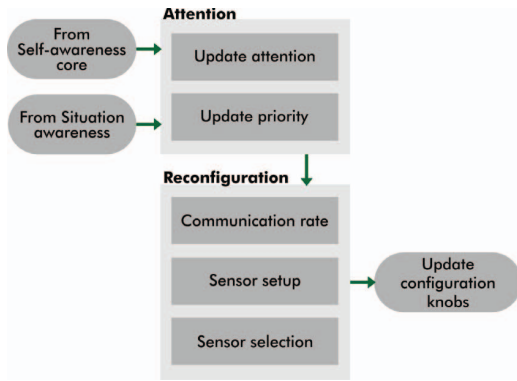
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Fig. 4. Attention and Reconfiguration diagrams

Fig. 5. Priority score chart

information and hints regarding the state of the patient and environment from the *Self-awareness core* and the *Situation awareness* components and chooses an optimal setting for meeting the requirements while offering efficiency and reliability to the system. It then transmits proper commands to the *Configuration* component in order to update (i.e., actuate) the properties of the sensor network. Figure 4 illustrates *Attention* unit which includes two main parts; First is the attention configuration which determines which parameters (i.e., sensors) should be monitored and how often. The second part is the priority list which is used to keep track of priorities and used for conflict resolution once the attention requirements cannot be met using the available resources at the moment. In such a case, the priority list determines which requirements are of more importance and need to be honored first and foremost, and which ones can or may be omitted in the case of insufficient available resources.

In our EWS system, we prioritise the attention based on the patient emergency level, patient activity, and the environmental situation, respectively. In other words, when a patient' health state is at higher emergency levels, the Attention unit allocates more resources for monitoring the patient, and conversely when the patient is in non-emergency situation, the module considers other parameters to opportunistically enhance system characteristics such as energy-efficiency. A sample prioritization method that we used in our experiments is shown in Figure 5. We define four levels of the emergency, five states for the activity, and four situations for the environments. In this method. we define a priority score between 0 to 100 for each combination of emergency level, situation, and activity. As shown in the figure, emergency level has highest and environment has lowest effect on priority score. These priorities then are mapped to the number of actuation states available in the reconfiguration component.

E. Reconfiguration

The *Reconfiguration* component receives the priority values from the *Attention* unit and maps them to the corresponding state of the sensor network. As demonstrated in Figure 4, each state in the sensor network is determined by the communication rate, sensor configuration setup (e.g., sampling frequency), and sensor selection (e.g., activation or switching to sleep mode). This component sends the selected state as sensor-network-understandable commands to update the configuration knobs.
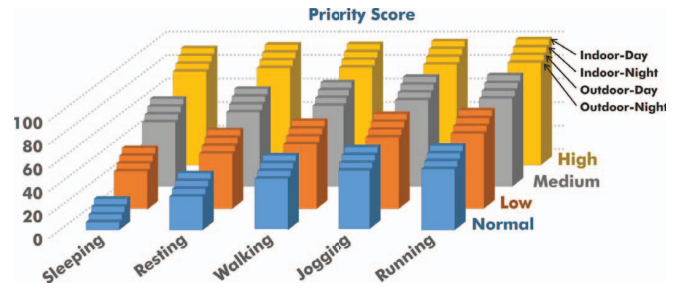
V. DEMONSTRATION AND EVALUATION

In this section, we describe the implementation of our self-aware solution for the remote patient monitoring system. We first present, how our system assesses the data confidence level, then show how we reconfigure and calibrate a generic EWS system in a real-time fashion by taking the patient's context into consideration, and finally demonstrate the energy efficiency gain offered by our self-aware closed loop edge controller for the body area sensor network. The system collects medical and activity data from the body area sensor network and environmental properties from another set of wireless sensors. The plausible range of data together with the rate of changes and the relation to the other parameters help enhancing the reliability of collected data. Patient activities and environmental data give an overview of the situation and help redefining the early warning score limits. The modified score reconfigures the system state to reduce energy consumption in the body area sensor network.

The body area sensor network consists of five sensors: 1) A SPO_2 finger grip sensor which provides the value of blood oxygen saturation and heart rate every second, 2) an airflow sensor to record respiration rate (we record its analog output with 100 samples per second), 3) a blood pressure sensor with arm cuff; for each measurement we continuously record the analog pressure signal for two minutes with 100 samples per second to calculate the systolic and diastolic blood pressure using the oscillometric method, 4) a 3D-accelerometer sensor to record patent's activity with 100 samples per second sampling rate, and 5) a temperature sensor to record body temperature with the same sampling rate as the heart rate and SPO_2 sensors.

The environmental sensors measure temperature and light, collecting samples once every minute. There is a micro-controller unit (MCU) in each set of sensors to collect and convert signals, send data to the RF module, and switch between states.

Adjusting EWS based on data reliability (confidence): The communication to a sensor can be faulty, or the sensor itself can be broken or detached from the patient. Therefore, in the self-aware core, we check the reliability of data and assign a degree of confidence by which the data and consequently the score assessments can be relied upon.

The algorithm consists of three different modules: checking the measured value to ensure (i) it is in a plausible range, (ii) it has plausible rates of change, and (iii) it corresponds with other vital signals (i.e., cross validity). Figure 6 shows the results of the three experiments, respectively for modules (i) to (iii). In the first experiment, a body temperature's value of $100°C$ was injected as a faulty value. Therefore, it gets tagged

as unconfident and abstains from the self-aware EWS (SA-EWS) calculation. While the SA-EWS correct shows the score *0*, the conventional EWS equals 3 at the beginning due to the faulty input and the absence of a validation system. Experiment 2 deals with the consistency of the input signals. The body temperature is initialized with a value of $36°C$ and then, after a short period of time, drops with a *rate of change* beyond the acceptable range. While the conventional EWS changes from 0 to 2, the system identifies the body temperature as unconfident and revises the SA-EWS score to 0. Finally, Experiment 3 shows the third module which works with abstracted data. The body temperature was set to a value which is equivalent to score *1* and all the other inputs where - time displaced - set to score *1*. After a while, when more than 50% of these signals have a non-zero status, the temperature is tagged as confident, and the SA-EWS becomes equal to the EWS. The details of the confidence evaluation method can be found in our previous work presented in [24].

Adjusting EWS based on the situation: In *Situation Awareness* module, we use the collected data from activity and environment sensors to find the situation of the patient. We define the environment as *day/night* and *indoor/outdoor* using temperature and light sensors and the system clock. We use the Geo-location service of the gateway smartphone together with the normal room temperature (18°C to 24°C) to indicate the indoor situation. We determine the day vs. night by comparing the time with approximate sunrise and sunset time in the local timezone. The intensity of light helps in determining is the patient indoor or outdoor. Furthermore, light intensity can be used to increase confidence level of determining sleeping of the potient. Finally, we utilize direction and amplitude changes in patient's body acceleration using a 3D-accelerometer sensor to determine the activity.

Then goal of the proposed self-aware health monitoring system is to improve the standard early warning score method by considering the fact that the patient is not in a standard clinical environment all the time. This module performs two main tasks: adjusting the scores' ranges in the EWS table based on the patient's activity and adapting the EWS calculation in the case of incorrect readings. The first task starts by calculating the normal early warning score and emergency level. Once an increase in heart rate, respiration rate, blood pressure or body temperature is observed, the system cross checks with the activity state. If this change is due to walking, jogging or running, we adjust the early warning score to avoid false alarms. The details of the self-aware modification of early warning score method can be found in our previous work discussed in [28]. Once a reliable score is obtained, we classify the score according to emergency levels. In this classification, a score 0 means a normal level, scores 1-3 indicate a low emergency level, scores 4-6 show a medium emergency level, and higher scores (> 6) represent a high emergency level.

As a case study, we use 8 hours of recorded data from a 35 years old healthy male subject whose state in practice should be detected as *Normal*. The first chart, from the top, in Fig. 8 shows the calculated scores using the original EWS table which issues several false alarms while the subject is running and jogging. The second chart in this figure shows the calibrated scores using self-aware EWS at runtime considering the state of the activity and environment which can be seen from the third and fourth charts. The results show that self-
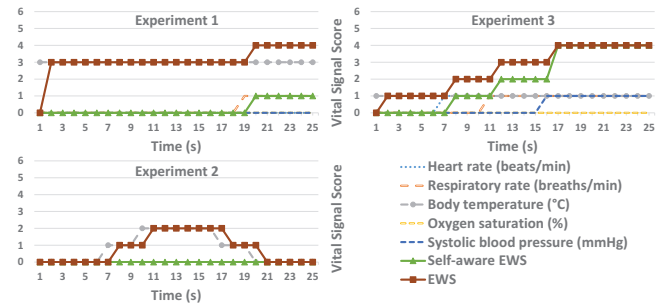

Fig. 6.   Enhancing the EWS using confidence. Adjusted EWS after reliability validation of the input data, avoids elevating EWS due to faulty data.

Emergency Level:	Score:0 Normal				Score:1-3 Low				Score:4-6 Medium				Score>6 High			
	Indoor		Outdoor		Indoor		Outdoor		Indoor		Outdoor		Indoor		Outdoor	
	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night
Sleeping	E	E	E	E	C	D	D	D	B	C	C	C	A	A	B	B
Resting	D	D	D	D	C	C	C	C	B	B	B	B	A	A	B	B
Walking	C	C	C	C	B	C	C	C	B	B	B	B	A	A	A	B
Jogging	C	C	C	C	B	B	B	C	B	B	B	B	A	A	A	B
Running	C	C	C	C	B	B	B	B	B	B	B	B	A	A	A	A

Fig. 7.   States look-up table derived from attention score

aware EWS correctly reports the normal and low emergency levels in 99% of the monitoring samples.

In addition to provide healthcare professionals with these values, the state of the patient is used by the Attention module to fine-tune the sensor network parameters to a more efficient state.

Optimizing energy efficiency using Attention: We use HM-11 Bluetooth low energy module to transmit the signals to an Android phone acting as the gateway. We measure the power consumption of the transmission process using a power monitor device. The results show that the power consumption of this module, when operating at 3.3V is in general at one of the following levels depending on the operation mode: 1) in standby mode, when the module is on but not sending data, the Bluetooth module consumes 26.2 mW, 2) in transmission mode, when the module sends data continuously with 115200 bit/second baud rate, it consumes 29 mW, and 3) in sleep mode the module uses 1.52 mW. Considering the power consumption of Bluetooth module, we define 5 different states (A to E) for the data transmission. As the volume and resolution of the required data changes with the situation of the subject, the sampling rate of the medical and activity sensors is divided into these five states in a way that the required data is provided while maximum number of standby/sleep modes is utilized. Considering five states of transmission with different bandwidth and energy consumption requirements, we map the output of the priority list shown in Figure 5 to a slot in one of the four lookup tables shown in Figure 7. After looking up a proper state, a new configuration state is sent back to the MCUs in the sensor network to update the transmission rate and activity mode of the transmission module. Table II shows the details of the data collection orders and power consumption of the each state. As the Bluetooth low energy module takes 1235 ms to wake up from the sleep mode, we use the standby mode for states A and B, and to get the benefits of the ultra low power sleep mode, we set non-continuous parameters sampling rate to be recorded every minute in other states.

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TABLE II. Description of defined states

| State	Respiration Rate Activity	Blood Pressure	Heart Rate, SpO2, and Body Temp.	Transmission Power Consumption
A	Continuous	Every hour in day Disabled in night	Every sec.	29 mW
B	2 min continuous 8 min OFF	Every hour in day Disabled in night	Every sec.	26.8 mW
C	2 min continuous 3 min OFF	Every 3 hours in day Disabled in night	Every min.	12.5 mW
D	2 min continuous 8 min OFF	Every 3 hours in day Disabled in night	Every min.	7 mW
E	2 min continuous 18 min OFF	Disabled	Every min.	4.3 mW
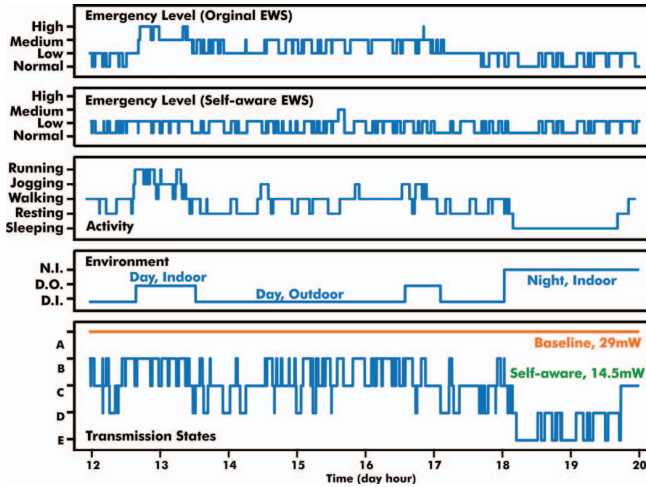
Fig. 8. Self-aware EWS system vs. conventional EWS system

The bottom chart in Figure 8 shows the achieved power saving due to closed-loop control of transmission states performed by the Attention unit for the same set of recorded data. We look up the results of self-aware EWS calculation, activity, and environmental situation using the mapped lookup tables shown in Fig.7 to adaptively adjust the transmission mode of the RF module of the sensor node. The chart shows that overall power consumption of the transmission is reduced by 50% to 14.5mW compared to a baseline non self-aware system which consumes 29mW.

VI. Conclusions

Early Warning Score (EWS) is a method to predict sudden health deterioration of patients suffering from life-threatening diseases to subsequently provide early diagnosis and treatments. Integration of health monitoring with ubiquitous IoT-based systems could enable patients to be monitored continuously not only in hospitals but also at home and at work. The traditional EWS method, however, is inappropriate for out-of-hospital patient monitoring due to challenging issues from both the user and system perspectives. In this paper, we introduced an IoT-based EWS system using the concept of self-awareness to target both perspectives. On one hand, our system offered a personalized and self-organized decision making for patients engaged in various activities in different environments. On the other hand, in this system, we proposed a self-awareness-enabled method to improve the system's energy efficiency and its confidence in its computed results, i.e. the EWS values. We demonstrated the benefits of our solution in a proof of concept full system implementation which reveals an improved level of data dependability and system energy efficiency compared to conventional open-loop systems.

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