Energy-Saving Adaptive Sampling Mechanism for Patient Health Monitoring Based IoT Networks

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Abstract. This paper proposes an Energy-saving Adaptive Sampling Mechanism (EASaM) for patient health monitoring in the Internet of Things (IoT) networks. EASaM is implemented in the biosensors to remove redundant data during monitoring the status of the patients. It operates in the way of rounds. There are two periods in the round. The emergency discovery and adapting the sampling rate of each biosensor are two main steps in EASaM. The NEWS is implemented at each biosensor to eliminate the repetitive sensed data before forwarding it to the coordinator. The sampling rate is modified after every two periods based on the status of the patient at the end of each round. We achieved several experiments based on real sensed data from the biosensors of the patients. The results explain that the proposed EASaM decreased the sent data up to 80.75% and 85% for the high-risk patient and low-risk patients and the energy consumption is decreased whilst keeping a good representation for the whole scores at the coordinator in comparison with other methods.

Keywords: Wireless Body Sensor Networks (WBSNs) · IoT · Adaptive sampling · Patient health monitoring · Emergency detection

1 Introduction

In recent years, the world faces an increasing number in the illness and patients. Moreover, wars and the relationships between the human and animals led to introduce and spread new kinds of viruses and unknown diseases such as coved-19. Consequently, this will make the work of doctors and nurses is very difficult [1].

Last years, providing health care for patients has received many advantages from governments and the world. They spent high costs to provide different services of health and applications [2]. The rapid advancement of IoT technology, medical sensors, and huge data strategies led to increase and emerge the healthcare systems that called connected healthcare [3, 4]. This technology allowed professionals to access patient data remotely and provided simple and inexpensive options for monitoring and tracking the patients wherever they were and at any time.

A. M. Al-Bakry et al. (Eds.): NTICT 2021, CCIS 1511, pp. 163–175, 2021.
https://doi.org/10.1007/978-3-030-93417-0_11

Typically, the healthcare systems are composed of biosensors that provide patients' monitoring. These biosensors collect the vital signs (of oxygen rate, respiration rate, oxygen rate, blood pressure, heart rate, and temperature) for the patients continuously and periodically and then send these sensed vital signs to the gateway for larger processing [3, 5]. The connected healthcare applications are facing some important challenges like saving the power of the biosensor devices to ensure a long time monitoring as possible for the patients, and speed up discovering of the patient's emergency and send it to the medical specialist to provide the suitable decision.

To deal with these challenges, this paper suggests an Energy-saving Adaptive Sampling Mechanism (EASaM) for patient health monitoring in the Internet of Things (IoT) networks. EASaM is executed in the medical biosensors to eliminate unnecessary data during controlling and observing the situation of the patients. It functions in rounds. The round includes two periods. The emergency detection and modifying the sampling rate of each biosensor are two main steps in EASaM. The NEWS is achieved at each biosensor to drop the repeated data before delivering it to the gateway. The sampling rate is adjusted after every two periods based on the situation of the patient at the end of each round.

The rest of this paper is arranged as follows. The next section explained the related work. Section 3 demonstrates the proposed EASaM Approach for Smart Healthcare in IoT networks. The simulation results and analysis are presented in Sect. 4. Section 5 introduces the conclusions and future work. The healthcare system is composed of a group of biosensors that are responsible for monitoring the patient situation and sensing the vital signs like respiration, oxygen, rate of heart, the pressure of blood, temperature, etc., then send it to the coordinator to achieve more analysis and processing [3, 5].

There are some important challenges in the Connected healthcare application such as: decrease the consumed energy of the biosensor devices to guarantee as long monitoring as possible for the patient and fast detecting of the patient's emergency and report it to the medical experts to provide the appropriate decision.

To deal with these challenges, this paper proposed an Energy-efficient Adaptive Sensing technique (EASeT) for Smart Healthcare in IoT networks. EASeT integrate between two energy saving approaches: data reduction with emergency detection of patient and adaptive sensing of the biosensor. The first phase aims to discover the emergency of the patient and eliminate the repetitive medical data before send it to the coordinator. The second phase achieves the adaptive sensing based on the similarity between the scores of the last two periods. The remainder of this paper is organized as follow. The related work is explained in the next section. Section 3 demonstrates the proposed EASeT technique for Smart Healthcare in IoT networks. The simulation results and analysis are presented in Sect. 4. Section 5 introduces the conclusions and future work.

2 Related Literature

One of the effective solutions in hospitals is to use the connected healthcare to save and process the sensed vital signs of the patients to make the appropriate decision to save their lives. Some related work is focused on compression methods to reduce the huge data [6, 7], aggregation [8, 9] and prediction methods [10]. In [10], the authors propose a technique named PCDA (Priority-based Compressed Data Aggregation) to minimize the medical sensed data. The authors employed compressed sensing with cryptography to compress the data while saving the quality of received data.

The authors in [11–13] presented an adaptive sampling with risk evaluation to decide for monitoring the patients by WBSNs. They proposed a framework to gather medical data by the biosensors and then introduce the risk of the patient using fuzzy logic. Finally, the presented an algorithm for deciding according to the level of patient risk. Shawqi and Idrees [1, 14] introduced a power-aware sampling method using several biosensors to provide the risk of the patient and the best decision to notify the medical experts. First, multisensor sampling based on the weighted scores model is introduced and then they suggested a decision-making algorithm that applied at the coordinator. The works in [15–19] proposed adaptive sampling approaches for WSNs. They have employed similarity measures and some data mining techniques to measure the similarity between two data set of two periods so as to change the sampling rate accordingly. In [20], the authors combine two efficient methods: divide and conquer (D&C) and clustering. They applied the D&C at the sensor nodes and then they applied the enhanced K-means at the cluster node to remove the redundant data and save energy before sending it to the sink. The authors in [6, 7] proposed lossless compression methods for compressing EEG data in IoT networks. In [6], they combine the fractal compression method with differential encoding. In [7], the authors combine Huffman encoding and clustering to further reduce compressed data before sending it to the IoT network.

The authors in [21] proposed three main methods that can be executed at the s-Health architecture, namely, divided in-network processing and resource optimization, event detection and adaptive compression, and dynamic networks association. The first method optimizes medical information transport from the edge node to the healthcare supplier, however taking energy efficiency and application's goodness-of-service request. The second method uses edge computing capabilities to demonstrate an effective data transit architecture that ensures high reliability and rapid emergency reaction. The third method leverages heterogeneous wireless networks within the s-Health architecture to perfect various applications' requirements while optimizing energy consumption and medical data delivery.

The authors in [22] proposed fixing the problem by taking advantage of rapid innovations in the fields of mobile phones, sensors and wireless technology to get better health systems is a critical method. M-Health system accommodates the usage of an edge device to communicate medical data through the wireless network across the m-Health station to diagnose and control the situation of the patient as quickly as possible.

3 EASaM Mechanism

This paper suggests an Energy-saving Adaptive Sampling Mechanism (EASaM) for patient health monitoring in the Internet of Things (IoT) networks. EASaM is executed in the medical biosensors to eliminate unnecessary data during controlling and observing the situation of the patients. It functions in rounds. The round includes two periods. The emergency detection and modifying the sampling rate of each biosensor are two main steps in EASaM. The NEWS is achieved at each biosensor to drop the repeated data before delivering it to the gateway. The sampling rate is adjusted after every two periods based on the situation of the patient at the end of each round. Figure 1 shows the Wireless Body Sensor Network model that used in this paper.

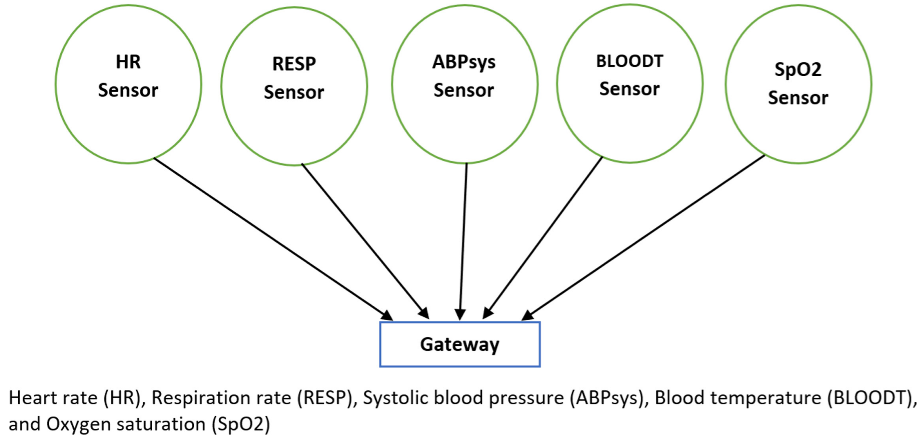

Fig. 1. Wireless body sensor network model.

3.1 National Early Warning Score

The medical staff in the hospital utilizes a physiological scoring system named National Early Warning Score (NEWS) to check the situation of the patients to provide the appropriate medical attention and the proper care for the cases with high levels of risk. There are six physiological parameters included in the NEWS that exhibit this system of scoring such as respiratory rate, oxygen saturation, temperature, systolic blood pressure, pulse rate, and awareness level or new contingency [23]. The main feature of NEWS is its simplicity in determining the risk level of the patient using the suitable scores for each type of biosensor. By scoring the sensed values of these biosensors, the NEWS can determine the status of the patient [24]. EASaM mechanism will apply NEWS at each biosensor. NEWS is displayed in Table 1 [25].

Table 1. NEWS (National Early Warning Score).

Physiological parameters	3	2	1	0	1	2	3
Respiration rate	<=8		9–11	12–20		21–24	>25
Oxygen saturation	<=91	92–93	94–95	>=96			
Any supplemental oxygen		Yes		No			
Temperature	<=35		35.1–36.0	36.1–38.0	38.1–39.0	>=39.1	
Systolic BP	<=90	91–100	101–110	111–219			>=220
Heart Rate	<=40		41–50	51–90	91–110	111–130	>=131
Level of Consciousness				A			V, P, or U

3.2 Emergency Detection of the Patient

In medical applications, the measurements of the patients are sensed using several biosensors (e.g., Oxygen Saturation, Heart Rate, Respiration Rate, etc.) located on the body of the patients. These medical sensors send in the periodic way each sensed measurement to the gateway. The gateway receives huge sensed measurements in each period. Hence, the data reduction at each medical sensor is essential before transmitting them to the gateway. Applying data reduction at the biosensors can save energy and extend the lifetime of the monitoring system. Moreover, it can reduce the volume of received data at the gateway to facilitate the analysis to provide an accurate decision about the situation of the patient.

According to NEWS, the medical sensors send to the medical staff just the measurements with scores larger than 0. The measurements of the normal state of the patients will not be transmitted to the gateway. It is clear that periodic monitoring for the situation of the patient will be reduced as well as the transmitted measurements to the gateway are decreased. Finding the relations among the sensed measurements per period before forwarding them to the gateway can participate in solving this problem.

This paper applied the algorithm of emergency detection for the patients at every medical sensor inspirited from [14] with some adjustments to test the scores of sensed measures and forwarding the ones with scores higher than 0. The emergency detection approach is presented in Algorithm 1.

Algorithm 1 Emergency Detection of Patient

```
Input: MR: Gathered measures in one period
Output: FM: Forwarded measures, SR: scores for forwarded measures
P_s ← NEWS(MR1)
FM ← FM ∪ MR1
SR ← SR ∪ P_s
ForwardToGateway(MR1)
EnergyUpdateForBiosensor()
For each sensed measure MRi ∈ FM do  // i = 2,3, …, N
    C_s ← NEWS(MRi)
    If  C_s ≠ P_s then
        SR ← SR ∪ C_s
        FM ← FM ∪ MRi
        ForwardToGateway(MRi)
        EnergyUpdateForBiosensor()
        P_s ← C_s
    endif
endfor
return FM, SR
```

To further understand the emergency detection technique, an illustrative example will be presented. Suppose there are ten measures of Respiration Rate medical sensor and the period size T = 10, MR = [16, 16, 14, 10, 11, 11, 21, 22, 24, 25]. By using

NEWS, the score's vector of MR measures is SR = [0; 0; 0; 1; 1; 1; 2; 2; 2; 3]. The forwarded measures by the medical sensor are [9, 15, 20, 24]. Only the critical measures and the first measure (even if it was 0) are forwarded to the medical expertise by the biosensor.

3.3 Adapting Sensing Frequency

The accumulated sensed measures of every medical sensor are time-correlated according to the situation of the patient. Consequently, when the patient's situation is stable, a lot of measures would be transferred to the gateway. There are three levels of risk for the patient: (1) low risk represents the normal case of the patient that wants low care by the medical staff. (2) Medium risk represents the middle case between the critical and normal situation of the patient that wants high care by the medical staff, and (3) high risk represents the severe illness cases of the patient that needs consecutive monitoring.

The sensed measures by the medical sensors are time-correlated especially in the cases of high or low risk. Therefore, sending a large volume of sensed measures by the medical sensors leads to spending the energy and increase the load on the medical staff. To get rid of this problem, it is possible to adjust the sampling rate of the medical sensor during sensing the measurements and according to the situation of the patient.

The proposed sampling algorithm in EASaM operates in the way of rounds, where each round includes two periods. Hence, the similarity rate should be calculated by the sampling algorithm between the scores of the measures of the two periods. The edit distance similarity measure is used to calculate this similarity between the two periods. Edit Distance (ED) is a measure of similarity that calculate the distance between two strings. It is also named Levenshtein distance [26]. Algorithm 2 shows the dynamic programming algorithm for computing the edit distance between two sets of data.

Algorithm 2 Edit Distance

```
Require: Mset1, Mset2: measures for two sets of 2 periods.
Ensure: Mdp: distance between the Mset1 and Mset2.
Mdp ← 0
For i ∈ Len(Mset1)+1 do
    For j ∈ Len(Mset2)+1 do
        if i = 0 then
            Mdpi,j ← j
        else if j = 0 then
            Mdpij ← i
        else if Mseti-1 = Msetj-1 then
            Mdpi,j ← Mdpi-1,j-1
        else
            Mdpi,j ← 1 + min(Mdpi,j-1, Mdpi-1,j, Mdpi-1,j-1)
        endif
    endfor
endfor
return MdpLen(Mset1), Len(Mset2)
```

Function Len(x) return the length of the set x. The time complexity of the edit distance is Θ(Len(Mset1), Len(Mset2)) and the storage complexity is Θ(Len(Mset1), Len(Mset2)) and this can be improved to Θ(min(Len(Mset1), Len(Mset2))) by observing that the algorithm at any instant requires two columns (or two rows) in the memory storage. Algorithm 3 presents the adaptive sensing rate achieved at every medical sensor at the end of the round.

Algorithm 3 Adaptive Sensing rate Algorithm

Input: SM1, SM2: two measures' sets for 2 periods), ASmin: minimum sensing rate, ASmax: maximum sensing rate

Output: ASrate: new sensing rate

```
Dist ← Edit Distance (SM1, SM2)
Dist ← Length(SM1) - Dist
SimR ← Dist/ ASmax
APsamp ← (1 - SimR ) * 100
If  APsamp < ASmin then
        ASrate ← ASmin
Else
      ASrate ← (ASmax * APsamp)/100
endif
return ASrate
```

4 Simulation Results

The performance evaluation of the proposed EASaM approach is introduced in this section. The simulation results are conducted using a custom simulator based on the Python programming language. Real medical data are used during the simulation which is taken from the dataset named MIMIC (Multiple Intelligent Monitoring in Intensive Care) of PhysioNet [27]. EASaM is evaluated using some performance measures like energy consumption, the adaptation of sensing rate vs data reduction, and data integrity. To show the performance of the proposed EASaM, we achieve the comparison with the modified LED* [13]. The simulation is performed during 70 periods (two hours) where the period length is 100 s. The ASmin and ASmax are respectively 10 and 50 measures per period. The record 267n of the patient was used by EASaM during the simulation. The respiration rate medical sensor is used taking into account both high and low risks circumstances.

4.1 Data Reduction vs Adaptation of Sensing Rate

This experiment studied the sensing (sampling) rate modification of the medical sensor and the reduction in the transferred medical data. Figure 2 exhibits the collected results of the suggested EASaM and for two kinds of patients: normal (a) and critical (b) which are compared with modified LED* for the same kinds of patients (c) and (d).

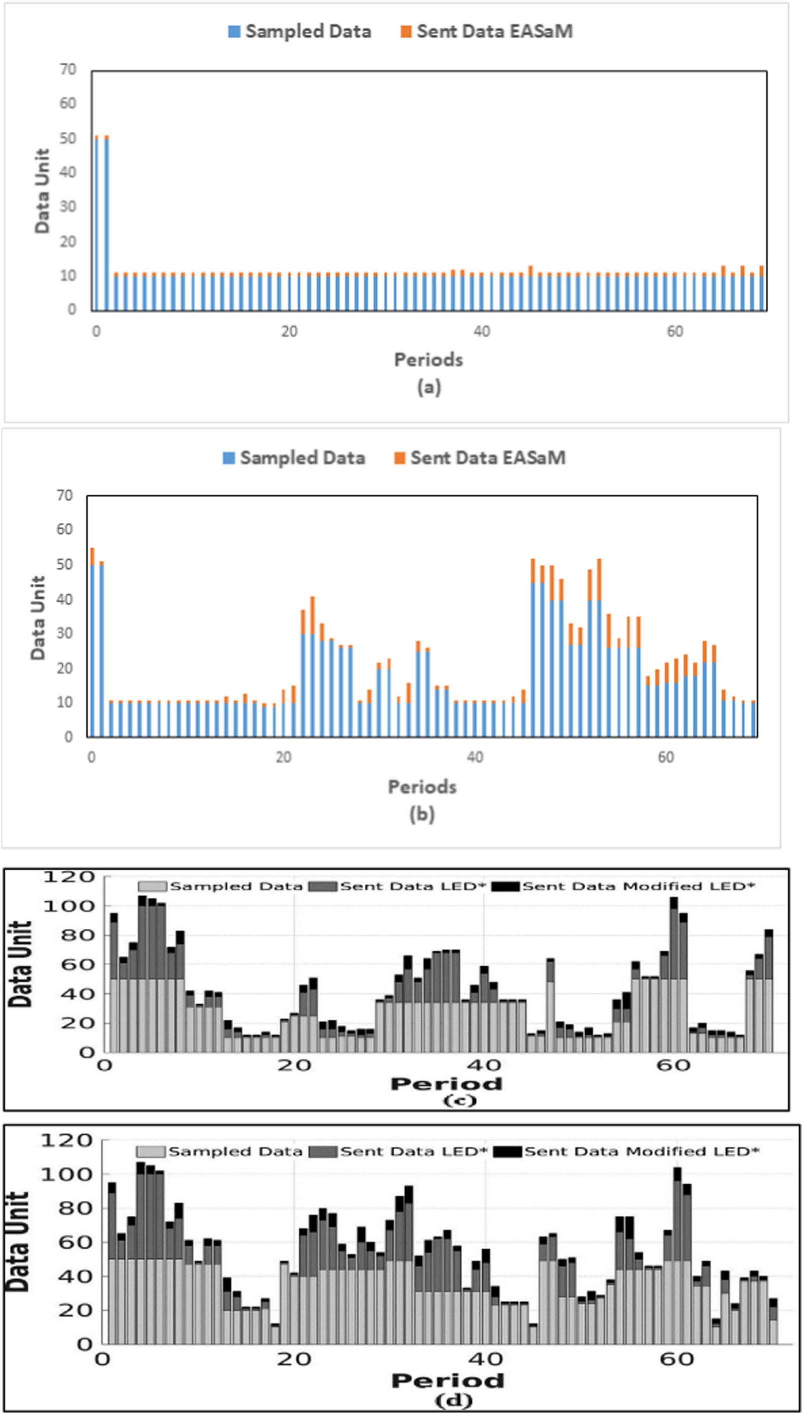

Fig. 2. Adaptation of sensing rate vs data reduction: a) low-risk patient, (b) high-risk patient of EASeT, (c) low-risk patient, and (d) high-risk patient of the modified LED* [13]. (Color figure online)

In Fig. 2(a) and (b), the orange and blue colours denote the number of sent medical data and the number of sampled medical data and respectively after executing the EASaM. In Fig. 2(c) and (d), the light grey and black colours describe the size of medical data and the number of sent data respectively after implementing the EASaM approach. The dark grey colour in Fig. 2(c and d) was ignored which represents the original LED method.

Figure 2(a and b) demonstrates that the size of medical data is altered to a minimum because of the similarity between the scores values of the medical data of the two periods in both cases of the patient: normal and critical. Furthermore, EASaM reduces the size of medical data using the emergency detection strategy by dropping similar data in each period before transferring it to the gateway for both cases of patients: normal and critical. Figure 2(b) shows that the transferred medical data is higher than the transferred data in Fig. 3(a) because it represents the case of the high risk. It can be seen from Fig. 2(a and b) that EASaM has greater performance than modified LED* (c and d) due to minimizing the size of data sent to the gateway and adjusting the rate of sampling of the medical sensor to the minimum.

4.2 Energy Consumption

The energy consumption at the medical sensor is studied taking into account the status of the patient (see Fig. 3). In this study, the EASaM used the same initial energy of the modified LED*, where the initial power of the medical sensor is initialized to 700 units. The consumed energy at the medical sensor for one sensed data is 0.1 and 1 respectively.

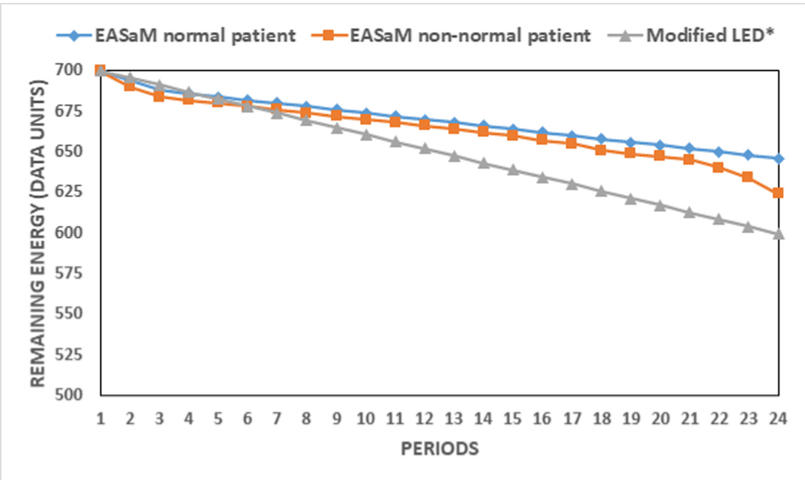

Fig. 3. Energy consumption.

The size of sensed and transmitted medical data has an important impact on the consumed energy at the medical sensor. EASaM approach will highly outperform the modified LED* by reducing the consumed energy at the medical sensor due to reducing the sensed and sent medical data to the gateway.

4.3 Data Integrity

This section studies the effect of the proposed EASaM on data integrity. EASaM presents the results for two cases: normal and critical patients (see Fig. 4a and b), while the results of the modified LED* for a normal patient presented in Fig. 4c.

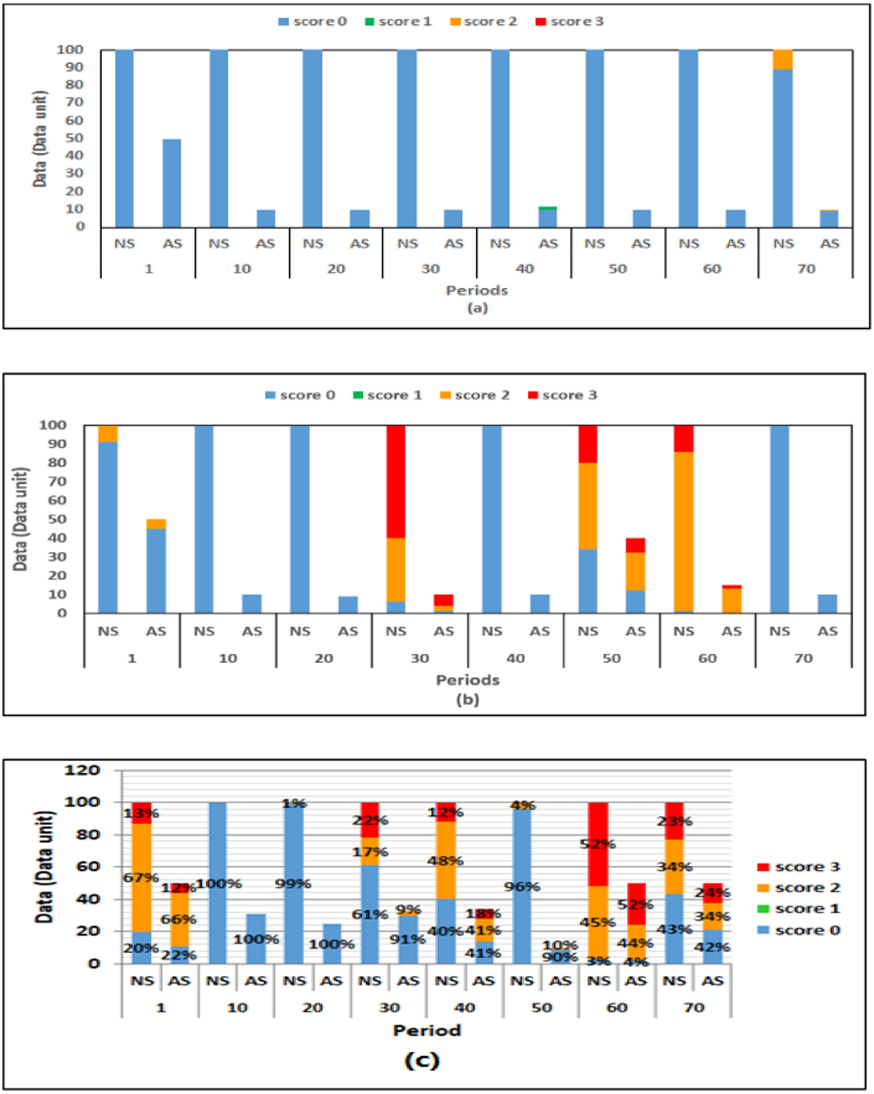

Fig. 4. Data integrity: (a) low-risk patient, (b) high-risk patient of EASaM, (c) low-risk patient of the modified LED* [13].

This experiment is performed with Adaptive Sampling (AS) and without Adaptive Sampling (NS) based on the captured medical data per period. It is obtained during scores distribution comparison (NEWS). The scores distribution for NS and AS is achieved for 8 elected periods of 70 periods to show the size of sensed medical data and their scores distributions at the medical sensor. The EASaM decreases the captured medical data for a normal patient in these selected 8 periods up to 85% (see Fig. 4a) compared with modified LED* (see Fig. 4c) that decreases the same captured medical data for the same patient up to 64.5%.

In the normal case of the patient, the kinds of scores are restricted to the score 0. This led to a large decrease in the captured medical data of the medical sensor. Furthermore, the EASaM decreases the medical data for the elected 8 periods up to 80.75% while keeping a proper description of whole scores at the gateway. Therefore, it can be noticed that EASaM guarantees a suitable level of data integrity of the captured medical data whilst preserving all scores without waste at the gateway.

5 Conclusion and Future Work

This paper proposed an energy-saving Adaptive Sampling Mechanism (EASaM) for patient health monitoring in IoT networks. EASaM achieves two main steps: emergency detector and adaptive sampling at each medical sensor. The conducted results show that EASaM is better than modified LED* in terms of energy-saving, data reduction, and data integrity. We plan in the future work to extend the work to achieve multisensor sampling using machine learning and decision support at the gateway to decide the status of the patients.

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