Self-Adaptive Sampling Rate to Improve Network Lifetime using Watchdog Sensor and Context Recognition in Wireless Body Sensor Networks

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ABSTRACT:
Todays, Wireless Body Sensor Networks (WBSNs) are used as a useful way in health monitoring. One of the most important problems regarding Wireless Body Sensor Network (WBSNs) is network lifetime. This factor mainly relies on the energy consumption of sensors. In fact, during capturing vital sign data and also communicating them to the coordinator, the biosensors consume energy. In this article, we are interested to propose an energy efficient Adaptive Sampling (AS) rate specification algorithm to set the amount of sensed data. According to the National Early Warning Score (NEWS), the sensors gather data and detect emergency data. Two scenarios have been used; the first is utilizing context recognition to indicate the active and sleep sensors in different time slices and the second is using watchdog sensors for checking patient situation in critical condition. Simulation results show that the proposed method can save energy and increase network lifetime by up to 4 times more than the previous work. In addition, our methods allow on average 75% improvement in overhead data reduction while maintaining more than 90% data integrity.

KEYWORDS: Wireless Body Sensor Network, NEWS, Context, Lifetime.

1. INTRODUCTION

Nowadays, using Wireless Sensor Networks (WSNs) is one of the promising methods for controlling patient's situations. Many Wireless Sensor Network technologies are able to enhance different parts of human lives and also facilitate the daily life problems [1]. In fact, Wireless networks are used for different clinical fields, such as patient monitoring, emergency systems, health programs, continual illnesses and nursing care. These instances consist of heart rate measurement, blood pressure and blood oxygen level metering systems, health control systems, synthetic pacemakers, and hearing aids.

On one hand, since the elder population trend in the world is growing, some groups of smart care are necessary to check their health situations. Permanently monitoring of patients is considered as one of the main important points about these technologies. [2].

On the other hand, the sort of homes which is equipped with healthcare monitoring equipment can offer different monitoring and controlling methods for people's health in order to monitor and check vital signs and makes next decisions [3], [4]. Also, constant monitoring helps those of people who need to detect their emergency situation and show proper alarms for medical care [5]. There are many different advanced technologies which enhance this phenomenon such as Radio Frequency Identification (RFID), Bluetooth and ZigBee. [6]

Wireless Body Sensor Networks (WBSN) is a set of sensor which has been assembled on the patient's body in order to gather vital signs such as blood pressure, oxygen levels, and respiration rates. These kinds of sensors are wirelessly connected to each other as a network that is called wireless body sensor network. In fact, this network has an important duty to collect vital data, monitor and check patient's situation and finally

send data to the coordinator. WBSN presents a low-cost solution to check healthcare monitoring. This operation instantaneously and without interruption by sensors and periodically collects data and transmits to the central. In WBSN, it gathers required information by sensors, such as body temperature, heartbeat, blood pressure, ECG, EEG and then analyzes data in order to monitor and control. Shriveling elderly is of some functions which could be mentioned due to WBSNs and avoids the unnecessary hospitalization. On the other hand, recuing healthcare costs is considered as one of the positive points of utilization of WBSN. [7]

Assume a set of sensors implanted in the patient's body, so, monitoring has a direct relationship with sensing data or biotic symptoms and warning when captured data crosses a threshold. After sensing data from a patient, data must be sent to the coordinator which is on or near a patient's body. Many different tasks are executed by the coordinator such as gathering, merging and sending data and also sending its decisions to the sink node. Then the captured data are sent to the healthcare station [8].

There are two important problems regarding WBSN. The first one is energy consumption because of serial forwarding, and the second one is sudden changes in patient condition. In this paper, we suggest two different scenarios to improve energy consumption and monitor sudden changes in patient condition. The first scenario, is through adaptive sampling rate and human context recognition. It leads to energy consumption improvement and data reduction. The second one is using watchdog sensor to monitor physical changing in suddenly variation.

This paper is structured as follows. Section II presents the research background and motivation. In Section III, we describe WBSN and an Early Warning System (EWS) and also the behavior of the sensor node. In Section IV, an algorithm with the emergency detection mechanism and human context and watchdog sensor as the first scenario has been proposed. We present a new method for adaptive sampling rate as the second scenario in section V. Section VI gives experimental results. Section VII presents the conclusion of the paper.

2. RESEARCH BACKGROUND

This is worth mentioning that data collection is one of the main functions in WBSNs. So, many different types of research have suggested various adaptive sampling rate methods for saving the sensor's power, increase the network lifetime and keeping data accuracy [9], [10], [11], [31], [34], [36].

In [9], two Algorithms have been proposed, the first one is a Resuscitation Adaptive Sampling Algorithm (RASA), and the second one is the Compensation Adaptive Sampling Algorithm (CASA). Moreover, the

Adaptive Sensor Management Scheme (ASMS) has been suggested to utilize ASA, CASA, and RASA based on the energy of sensors. The main task of RASA is setting up low sampling rate and keeping the self-sustainability, when the energy of sensors is low. Sensor nodes in CASA can revive some vitality by sparing the utilization vitality when the reaping quality is great. ASMS scheme consolidates with these two calculations. ASMS scheme divides the sensors of WSN into three classes as indicated by the Current vitality state and Current vitality reaping quality. Nodes in each class can be connected to distinctive ideal examining rate to accomplish the self-maintainability. Reproduction demonstrates that ASMS can spare utilization vitality, the most extreme and self-assured self-sufficiency nodes.

A detecting rate control plan is proposed for increment information determination without expanding the quantity of power outage nodes in vitality collecting remote sensor systems [10]. In the proposed plot, every node chooses a pressure calculation and alters the detecting rate to assemble more information while the node works legitimately. At the point when a node is evaluated to have additional vitality, it accumulates extra information. Conversely, when it is evaluated to be depleted, it accumulates less information to spare vitality. It additionally chooses a fitting pressure calculation as per the pressure proportion of the chosen calculation changes to diminish the workload of a middle of the road nodes. A test result checks that the proposed scheme assembles more information with a lower number of power outage nodes than different plans.

[11] proposed a new method to reduce energy consumption and maintaining the data quality. In this method, devices can set data rate from a minimum to maximum frequency to monitor the physical changing. Moreover, this technique helps to reduce many different useful parameters such as energy consumption, bandwidth resources, and data transmission. Results show that the suggested algorithm can save energy consumption while keeping the data accuracy.

Rechargeable sensor systems which are powered by reusable vitality are promising for ceaseless information benefit. Due to the time-fluctuating qualities of collected vitality, the issue of information examining rate designation to boost the system execution is another testing issue. In [12], they were worried about how to adaptively choose the information inspecting rate to amplify the information nature of all sensor nodes. To solve this issue, they divided the information inspecting rate portion into two stages to decouple the vitality and information examining rate. To begin with, they proposed a vitality allotment calculation (EAA) to distribute the measure

of vitality that is permitted to be utilized by every sensor node in every interim, so all sensor nodes cannot become short on their battery vitality and can store more vitality into the battery amid the reviving time frame. At that point, they demonstrated information testing rate distribution calculation (RAA) to allot the ideal information examining rate for every node. At last, they conducted extensive tests using genuine gathered information to assess the execution of the proposed calculations.

One of the important aspects regarding all algorithms related to adaptive sensing is keeping accuracy of sense. In [13], authors suggest an adaptive sensing scheme for WSNs which keeps the estimation accuracy of sensing events. The method proposed uses WSN context and physical parameters in order to reduce sensed data which leads to energy consumption reduction. In fact, decreasing sensing data and energy consumption are the advantages of LiteSense technique while maintenance of the estimation correctness of sensing data. In [14], they proposed an Adaptive Method for Data Reduction (AM-DR). Their technique depends on a curved mix of two decoupled Least-Mean-Square (LMS) windowed channels with various sizes for assessing the following estimated esteems both at the source and the sink node to such an extent that sensor nodes need to transmit just their prompt detected qualities that stray fundamentally (with a pre-characterized edge) from the anticipated qualities. The conducted tests on true information demonstrate that their approach has possessed the capacity to accomplish up to 95% correspondence diminishment while holding a high precision. In [15], authors proposed a data-conscious energy saving method based on (Cluster head) CH. In this technique, it is tried to use relation between sensor node of capture data and data trend in neighboring sensor nodes to reduce the data transmission. The data has been reduced by a prediction algorithm which is done by the ARIMA model. Each round, the data model predicted is compared to the observed data. If there is dislodgement beyond the special threshold at that place, nodes send a difference of information to the CH. The data differences collected by the CH are compressed with the use of PCA technique. The compressed information is sent to the sink node afterward. Using its method, a widespread quantity of redundant information transmission is cut off. The method also keeps the collected data's accuracy inside the predefined error threshold. Using information reduction-based power conservation technique, this consequence reduced data collision. Since compressed Sensing (CS) is one of the methods to improve energy efficiency of data collection in WSN, [16] suggesting an ideal approach for CS-WSN where we utilize a dictionary that learns along adaptive sparse training data. The proposed

method achieves minimum reconstruction frenzy by accounting changes into the data sparsity while data is able to be delivered to the sink along low energy consumption thereby improving electricity efficiency.

In the following, a new technique based on data fusion and Hidden Markov Model (HMM) is adapted. In fact, the HMM runs on sensor nodes as separately and merges captured data to transmit. It leads to efficient transmission and finally improves performance and energy consumption by sensor nodes which have been proposed in [17]. Since the data transfer period in WSN by sensors nodes is one of the main problems leading to increase of energy consumption, [18] presented a new approach based on data reduction for wireless body sensor networks. They used an algorithm to adapt the sampling rate using variances through statistical tests and also two functions including set-similarity and distance functions. The results showed that the proposed method reduces the number of acquired samples.

Many proposed methods in literature have done the adaptive sampling rate in good form, most of these researches have focused the same way [9], [10], [16], [18] and are according to current situation of sensor nodes in current round in order to estimate adaptive sampling rate for next round. Some of them [11], [13] have tried to keep data accuracy; in fact, they have focused on data. In fact, few researches have done to estimate sampling rate based on current round information to change sampling rate in critical situation. Moreover, many of researches use sensors just for reading information, and they do not consider activity or context of patient for capturing information in order to prevent extra data to coordinator.

3. WIRELESSs BODY SENSOR NETWORK AND HEALTHCARE MONITORING

In the following, we illustrate the design of a WBSN and the conduct of the nodes. We accept that a WBSN is used on a patient's body. The WBSN is made out of biosensors, every single sensor detects an indispensable symptom, that it has been pointed as a component. A node is characterized as a customary sensor furnished with those nodes that screen key marks. The part of every node is to gather estimations in an intermittent way and send them to the facilitator to play out the information combination and basic leadership. An organizer can be a particular restorative gadget, a cell phone, a PDA, and so forth. Additionally, it acts like a door to different systems. We trust that the battery of this capable gadget can be effectively energized or supplanted, at that point, it can be considered as a gadget unhindered by power and registering assets. Consistent with above lines, it is conceivable to influence a tradeoff between the vitality

of this gadget and the lifetime of the restricted vitality to body sensor nodes.

A. Determination level of criticality of patient

An Early Warning Score System (EWS) is a guideline utilized by crisis medicinal administrations staff in clinics to decide the level of criticality of patient circumstance. NEWS is utilized as an orderly convention to gauge basic physiological parameters in all patients in order to permit early diagnosis of those exhibiting an intense ailment or who are decaying [19].

A typical sound range is characterized for each imperative sign. Estimated esteem outside of this range has designated a score which is weighted and shading coded on the perception diagram as indicated by the extent of deviation from the ordinary range. The weighting shows the seriousness of the physiological aggravation. Fig. 1 indicates national EWS (NEWS) utilized as a part of U.K. [20] Declaring that we have utilized it as a part of our test tests and cases. In the following area, we will indicate how we utilize this EWS in a nearby crisis recognition calculation.

We have two different scenarios to reduce data and energy saving and also drastic changing in patient's situation: adaptive sampling rate using chi-square and Lagrange and also using watchdog sensor and human context recognition.

B. Suggestion method
B.1.The First Scenario: human Context recognition and Local emergency
B.1.1. Human context recognition

A human context recognition system utilizes wearable sensors, misuses sensors flags that allow us checking a client and his condition keeping in mind. The end goal is to construe continuous errands and living conditions. As described in Table 1, human setting examination incorporates both individual setting acknowledgment (dust-level, location, social interaction) and natural setting examination (e.g. area, clean level, social collaboration). The cognizance of the individual and ecological settings is of incredible significance to enhance the patient pursue for therapeutic and prosperity usages. [21]

Fig.1. National Early Warning Score (NEWS).

Table 1. Human context recognition.

Human Context	Context type	Sensor type
Individual	Emotion, Activity, health status	temperature, gyroscope, EMG, blood pressure, ECG, , Accelerometers
Environmental	Location, place, noise-level, pollution, social interaction	GPS, Wi-Fi traces, CO_2 sensor, luminosity, microphone, Bluetooth scans

C. Local Emergency Detection using watchdog sensor and human context recognition

In a usual wireless sensor network, each node gathers data and sends them in accordance with the coordinator in an interim manner. Thus, a big quantity of records is gathered then dispatching every length in accordance with the coordinator node. Therefore, we must determine a scheme that decreases the volume regarding information whilst guarantees integrity between the same epochs then optimizes information transmission in accordance with minimizing the strength destruction concerning nodes. The forward

instinct is to send the advance captured excuse throughout duration namely well as whole the imperative measurements in accordance with the coordinator as proposed by [22] then recognize namely LED algorithm. Detection concerning extraordinary conditions is allowed by providing a native caveat law regarding each sensor. Thus, the rating concerning each captured data is calculated, which permits us to notice someone emergency promptly and is locally represented by a rating extraordinary beside zero. However, statistics transmission executes keep it optimized. Indeed, so a chance is detected now then it

is not continually beneficial after ship of all the quintessential data. For example, assume a node shooting the breathing degree is going for walks the LED algorithm. This recent wish sends massive quantity concerning integral data if the respiratory dimension on the patient is odd because of a lengthy time. This suit is entirely frequent into troubled health situations where the entire records sensed with the aid of the biosensor nodes are essential then extra. So, we endorse to adjust LED algorithm within kilter in conformity with in addition to optimize facts

transmission and also limit the electricity destruction over the biosensor nodes or extend their lifetime.

Moreover, Modified LED* has been proposed by [48] to reduce sampling data. In fact, modified LED* send data if the sensed data differ from sent data and also it tries to convert data afterward to index using EWS. It reduces transmission data across the network. In the suggested algorithm for collecting data via sensors, it has been tried to reduce sensed data and data transmission over the network to reduce communication.

Algorithm 1: Advanced LED (ALED)

Input: R_t (Sampling Rate value).
Loop
For i=1 to period number
All sensors are in sleep mode exception BP sensor (watchdog sensor)
Takes first measurement r_0
Sending r_0 as the first measurement
Getting score S of r_0
Taking values r_i at R_t Rate
Gets score S_i of measurement r_i
If Context is sleeping (or other context) then
//---------------------------------- watchdog sensor
If BP > threshold then
Awake up other sensors
Else
All sensors go in sleep mode exception BP sensor
End for
If Si! =S then
Sends measurement r_i
$S = S_i$
End if
**End if**
Until Energy < 0 do

Therefore, we suggest human context recognition and watchdog sensor in a new algorithm in the first scenario (Algorithm 1). Assume a patient who has not any problems to monitor when the patient is in sleep (or in specific GPS in home and some stuff like that). Now, we just monitor blood pressure through watchdog sensor since this feature is important for many patients. We monitor blood pressure when patient is in sleep and if there is a problem other sensors wake up and send data to coordinator, otherwise all sensors are in sleep mode and just send blood pressure sensor. In fact, blood pressure is the main feature to detection emergency patient's status via watchdog sensor. This mater helps to reduce sensed data and traffic. Moreover, using watchdog sensor reduces the number of communications between sensors. Finally, reduction of communications leads to energy consumption of nodes. The main reason behind the matter is that, the amount of energy consumption for sending decreases contrary to remaining energy that increases.

Moreover, the Advanced LED Algorithm optimizes data transmission over the network by data sensing using human context recognition.

Assume s = {v0 ,...,vn } is a collection about sensed information at a R_t degree during a duration p belonging in conformity with a given function and s_{scores} = {score(v0),...,score(vn)} is the sequence about theirs corresponding rankings computed by an EWS. The sensor sends data v_i only when its score (score (v_i)) is different beyond the rating over the previous sent records in the identical duration. Therefore, the transmission is optimized via getting rid of the transmission regarding consecutive sensed information forlorn the same score while preserving data morality by sending records of each age, an instant rating is detected. For example, assume s = {v0 ,v1 ,v2 ,v3 ,v4 ,v5 ,v6 ,v7 } is a series of 8 sequent values for an attached specification, s_{scores} = {1, 1, 0, 2, 2, 2, 2, 0} is the series regarding the analogous sequent scores. Via

algorithm 2, it is possible to just send {v0, v2, v3, v7} to the coordinator for checking patient situation.

However, using Advanced LED (Algorithm 1), it might not send data due to using watchdog sensor. In fact, captured data will be sent when watchdog sensor detects emergency situation, else it will not send it to the coordinator and also in this situation rest of sensors of watchdog are expected to be in sleep mode. The Modified LED* improves transmission of data without using the human context in data sensing across the
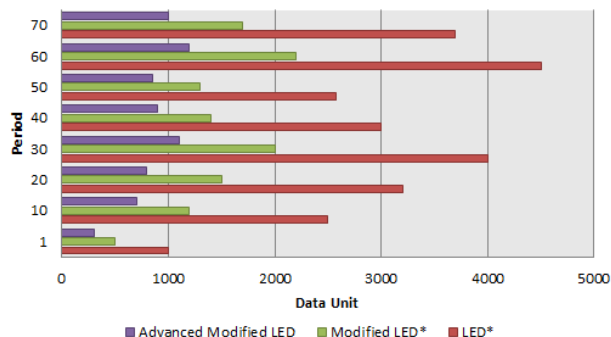
network. In the following section, it is tried to show how node's energy are saved via human context recognition and adaptive sampling rate.

As shown in Fig. 2, we utilize sleeping. In fact, watchdog sensor senses have good situation in fig when patient is in sleeping situation 2(a) and watchdog sensor detects critical situation in fig 2 (b). The amount of traffic decreases in fig 2(a) by 75% and in fig 2 (b) is about 40%.
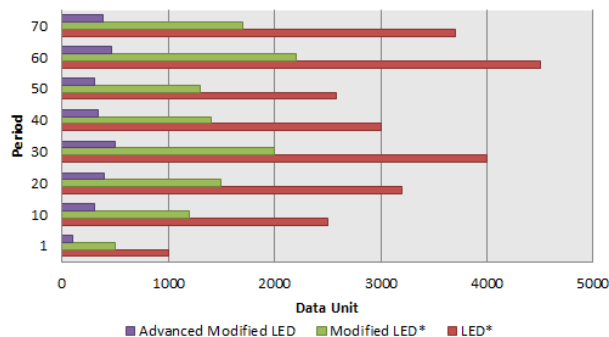

Fig.2. Captured data using watchdog sensor and human context. (a) Normal situation (b) Critical situation

4. THE SECOND SCENARIO: ADAPTIVE SAMPLING RATE USING LAGRANGE FUNCTION AND CHI-SQUARE TEST
A. Adapting Sampling Rate

Therefore, we suggest human context recognition and watchdog sensor in a new algorithm in the first scenario (Algorithm 1). Assume a patient who has not any problems to monitor, when a patient is in sleep (or in specific GPS in a home and some stuff like that). Now, we just monitor blood pressure through watchdog sensor since this feature is important for many patients. When the patient is in sleep we monitor blood pressure and if there is a problem, other sensors wake up and send data to coordinator, else all sensors are in sleep mode and just send blood pressure sensor. In fact, blood pressure is the main feature for detection of emergency patient's status via watchdog sensor. This matter helps to reduce sensed data and traffic. Moreover, using a watchdog sensor reduces the number of communications between sensors. Finally, reduction of communications leads to the energy consumption of nodes. The main reason behind the matter is that, the amount of energy consumption for sending decreases contrary to remaining energy that increases. Moreover, the Advanced LED Algorithm optimizes data transmission over the network by data sensing using human context recognition.

B. Adaptive and Chi-Square

The Chi-square test is a standout amongst the most helpful measurements for testing theories when the

factors are ostensible, as regularly occurs in clinical research. Not completely like most insights, the Chi-square ($\chi2$) can give data not only on the hugeness of any watched contrasts, but also gives point by point data precisely, which classes represent any distinctions found. Consistent with above lines, the sum and detail of data in this measurement can give renders a standout amongst the most helpful devices in the specialist's various accessible investigation instruments.

C. Patient Risk Vs Sampling rate

According to the primitive definition of risk level, as shown Fig. 3, two different states exist and are introduced for patient's risk level. In fact, risk level specifies patient's situation in order to monitor with or without emergency state. The risk level depends on the patient's situations and his disease. The patient's risk level value can be variable from 0 to 1. The smallest values for a patient's risk level value means low critically level and thus low sampling rate. On the other hand, high values for the patient's risk level value means high critically level that leads to high sampling rate by calculating the $\chi2$ value, which specifies the amount of changing in patient's status. In fact, if there is so much changing in captured data, it increases the amount of sampling rate to a high value (Maximum sampling rate). Else, it must be calculated. According to the mentioned notes, we plan to consider the patient's critical level as one of the main parameters for denoting an accurate sampling rate. As an important note, it urges to say that the proposed strategies should

not lead to low data accuracy, so the accurate sampling rate should be calculated which is described at the rest of the paper.
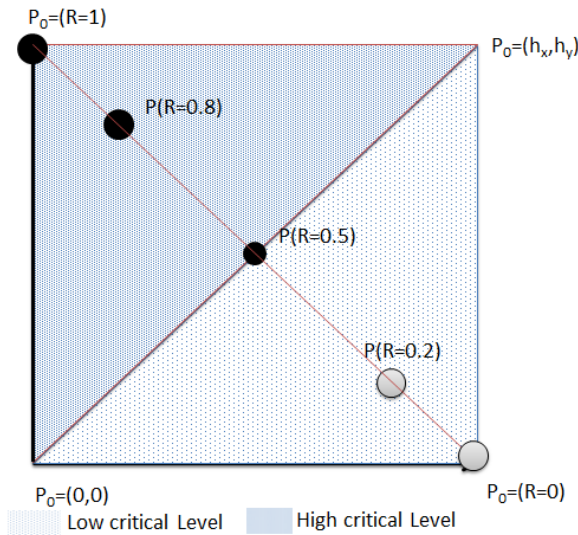

Fig.3. Relation between patient risk and sampling rate.

D. Calculating Chi-square

In order to calculate chi-square, first, we must complete a table in three main columns including; category, expected values and observed values. Then, it can proceed with calculating the χ^2 statistic to find out if the data sensed have high variation in the captured measurements. The formula for calculating a Chi-Square is:

$$\sum x^2 = \frac{(O-E)^2}{E} \tag{1}$$

Thus, the decision is based on the following.

1) If $\sum \chi^2 > X_{N-1,\alpha}$ the variance between periods are significant and the sampling rate is balanced to the maximum sampling rate.
2) If $\sum \chi^2 \leq X_{N-1,\alpha}$, the variance between periods is not significant; thus, the measures captured in the L periods are considered correlated (1 round = L Periods).

Note that in order to achieve$\sum \chi^2$, it requires Expected (E) and observed (O) values. Then we need data of L periods in every round (r). After that $X_{N-1,\alpha}$ must be calculated. $X_{N-1,\alpha}$ is a threshold that can be searched in the chi-square table based on N and α values. The N is degrees of freedom. The degree of freedom of an estimate is the number of independent pieces of information that went into calculating the estimate and α is the risk of the statistical test. Algorithm 2 describes the adaptive sampling rate algorithm at the sensor node based on the distribution data (Chi-Square test). For each round, every node decides to increase or decrease its sampling rate according to the distribution condition and the patient's risk. As long as the energy is positive, each node calculates the parameters $\sum \chi^2$ and $X_{N-1,\alpha}$; then, it uses the behavior Function in order to find its new sampling rate.

There are two suggestions for patient risk level and it has been proposed that low and high-risk levels can have values between 0 and 1. In fact, we define two risk levels:

Algorithm 2 (Second Scenario): Advanced LED with Adaptive Sampling (AS) Algorithm. (Advanced LED-AS)

Input: m, R$_{max}$
Output: R$_t$ (instantaneous sampling speed).
//--------------------------------(1 round = m periods)
//-------------- R$_{max}$ = maximum sampling rate
//--------------N = Number of rounds
R$_t$ ← R$_{max}$
Loop
For round =1 to N do
For period =1 to m
Run Advanced LED (Emergency Detection)
End for
Calculating needed parameters
If Condition is critical then
// set sampling rate in maximum value
R$_t$ ← R$_{max}$
Else
// Set Sampling Rate According to Behavior **Function**
R$_t$ ← Behavior (χ^2, X $_{(N-1,\alpha)}$, R, S$_{max}$)
End if
End if
End for
Until While Energy < 0

1) Level 1 "Patient with low risk," $0 \leq R < 0.5$: in this matter energy consumption of sensor nodes decreases. The main reason is that it does not need to monitor patient permanently, because the patient is in the low level of risk. These types of patients need monitoring including elderly people in caring houses, since they are in good shape.

2) Level 2 "Patient with high risk," $0.5 \leq R \leq 1$: this group of patients is in critical status and must be checked with a high level of risk. Some groups such as patients at home after a surgical intervention are the examples of these patients.

In order to find sampling rate we use results of chi-square test and the risk level R, and also the function (behavior) that is described by a Lagrange curve that crosses via four points as shown in Fig. 4. The four points are P0 (0, 0), P1 (bx , by) (checking point), and P2(hx , hy) (X $_{(N-1,\alpha)}$, S$_{max}$) and R(risk level).

In Fig. 2, we indicate how the bend of the Lagrange curve can be constructed while changing the Lagrange point (P1) organizes. As delineated, the bend is delimited by the first and the edge focuses, e.g., P0 and P1, respectively, while the checking point moves through the corner to corner of the square shape so as to control the application criticality. Consequently, when R differing somewhere in the range of 0 and 1, P1 will refresh its position based on the following function: [23]:

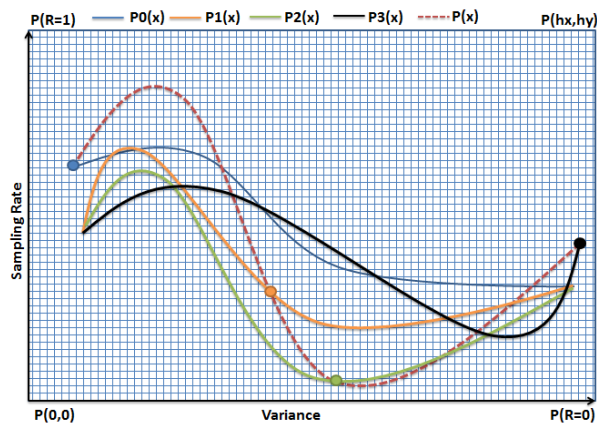$$Cr(R) = \begin{cases} b_x = -h_x R + h_x \\ b_y = h_y R \end{cases} \quad (2)$$

Fig. 4. Sampling rate adaptation using the behavior Functions.

The Lagrange interpolating polynomial is the polynomial P(x) of degree $\leq (n-1)$ that passes through the n points(x$_1$,y$_1$=f(x$_1$)), (x$_2$,y$_2$=f(x$_2$)),..., (x$_n$, y$_n$= f(x$_n$)) and is given by:

$$P(x) = \sum_{j=1}^{n} p_j(x) \quad (3)$$

Where

$$P_j(x) = y_j \prod_{\substack{k=1 \\ k \neq j}}^{n} \frac{x - x_k}{x - x_k} \quad (4)$$

Written explicitly,

$$P(x) = \frac{(x-x_2)(x-x_3)...(x-n)}{(x_1-x_2)(x_1-x_3)..(x_1-x_n)} y1$$
$$+ \frac{(x-x_1)(x-x_3)...(x-x_n)}{(x_2-x_1)(x_2-x_3)...(x_2-x_n)} y2 + ...$$
$$+ \frac{(x-x_1)(x-x_2)...(x-x_{n-1})}{(x_n-x_1)(x_n-x_2)...(x_n-x_{n-1})} y_n \quad (5)$$

Subsequently, the behavior function is defined based on the Lagrange as follows: Suppose the data set consists of 4 data points: P$_0$(x$_0$, y$_0$), P$_1$(x$_1$, y$_1$), P$_2$(x$_2$, y$_2$), P$_3$(x$_3$, y$_3$), the interpolation polynomial will have degree N − 1. It is given by: P(x) = □$_0$(x) y$_0$ + □$_1$(x) y$_1$ + □$_2$(x) y$_2$ +□$_3$(x) y$_3$, where the functions □$_i$(x) (i = 1, 2, 3, 4) are given by:□□

$$□_i(x) = \frac{(x-x_0)(x-x_1)(x-x_2)(x-x_3)}{(x_i-x_0)(x_i-x_1)(x_i-x_2)(x_i-x_3)} \quad (6)$$

5. SIMULATION RESULTS

We led various arrangements of simulations using MATLAB for confirmation our method. The goal of these reproductions is first to affirm our versatile information accumulation and discovery procedure, can recognize locally and effectively any crisis while contemplating alluring vitality preservation targets. Second, we demonstrate that our information combination strategy can adapt to our versatile information gathering and identification procedure. In line with above lines, in our recreations, we utilized genuine medicinal readings gathered trough MIMIC Database [24]. We have run the distinctive calculations amid 60 periods utilizing a Chi-square test (α = 0.05). In the following, it has been calculated the simulation via two fields: the temperature and the blood pressure. We have mulled over two unique circumstances for a patient, low and high risk, separately. We have assessed the application of the approach using parameters: 1) The time t (the number of periods), 2) m the number of periods per round, and 3) critical level (R). We use three metrics in our simulations: The first one is the amount of data reduction after each round. The second one is energy consumption. Finally, it uses data integrity to prove suggestive method.
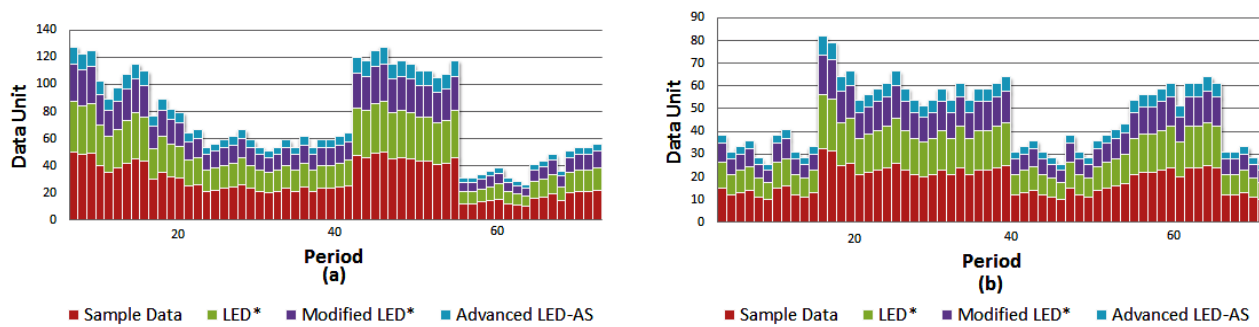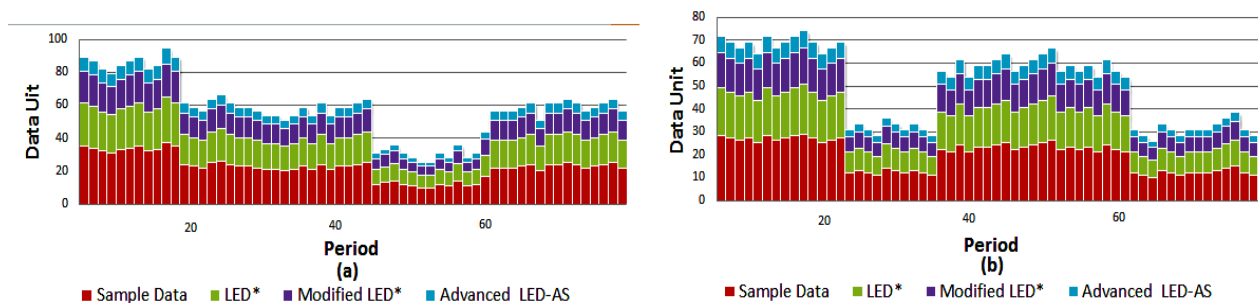
Fig. 5. Sample data (Round=2*Period).

Fig. 6. Sample data (Round=3*Period).

A. Immediate sampling rate and Data Reduction

In this section, we try to fix how our method is able to reduce and adapt its sampling rate based on the risk level of the patient. To simulate, there are two different situations, the patient with high risk and low risk, and (R=0.9) and (R=0.4), respectively. Moreover, a critical situation is another important and influential factor to simulate.

Figs. 5 and 6 show the amount of data which was sampled in each period. The amount of sampling rate has been considered about 50 in maximum mode and 10 in minimum mode. In the following, we compare the sent data among LED*, Modified LED* and Advanced LED-AS. It is necessary to say that modified LED* is coupled with the modified LED, adaptive sampling rate, advanced LED-AS combine advanced LED and adaptive sampling rate.

The suggested method adapts the sampling rate based on the patient's situation. Therefore, we try to analyze the outcomes obtained for a normal and critical patient. At the first glance, when comparing Fig. 5(a) and (b), it can be seen that the sampling rate for a patient in a critical situation is higher than a patient in a normal situation in similar period. For instance, at period 41, the inspecting rate is diminished to 43 on account of a basic patient; be that as it may, it is diminished to 11 when the patient is typical. In fact, a patient in a critical situation requires monitoring consistently with the high sampling rate, in order to record any changes that effect the health of patient.

Another factor which we have considered is the number of periods per round. Actually, this parameter specifies to the sensor nodes the number of periods which have passed, chi-square must be used to find sampling rate. Since the second parameter is the number of periods, we simulate our approach in 2 and 3 periods for any rounds. After that, we compare the results and it is shown in Fig. 5 and 6. As it can be seen, variation between sensed data increases when the period value increases from 2 to 3.

When there is high variation in the captured data from a patient, the sampling rate reaches maximum rate. For instance, in the event that we consider the blood pressure (basic case): when the period is 2, so round = 2 × period. In this way, when period is 2, the inspecting rate differs with the observing needs of the biosensor more decisively. This is expected to have a standard deviation between the estimation lower than the one when period is 3.

Third, we think about the amount of sent information in every period while receiving Modified LED* and Advanced LED-AS. We can observe that the two calculations limit the measure of information transmitted to the organizer. On account of the temperature, modified LED* and advanced LED-AS have a similar execution since the key sign presents stable typical score estimations over the 70 time frames. In both calculations, just the main detected information in a period is sent. Be that as it may, in the blood pressure sample, advanced LED-AS calculation beats Modified LED* and permits information

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diminishment to 75% (Formula 7) than Modified LED* and from the tested information. The purpose is that the breath rate of this patient is unusual and presents basic scores for most of the periods. Modified LED* sends all the basic detected information amid a period and, in this manner, it is not lessening the transmitted information contrasted with the detecting information for this situation. Be that as it may, advanced LED-AS sends just the estimations showing changes in the breath rate state and, subsequently, lessens excess and enhances the transmission. Information uprightness is examined afterward by demonstrating the effect of applying AS for gathering the information on the sensor node level.

$$Data\ Reduction = \frac{\sum_{i=1}^{Round} Advanced\ LED-Sensed\ Data}{\sum_{i=1}^{Round} Modified\ LED-Sensed\ Data}$$

(7)

B. Energy Consumption

It has been compared four algorithms (A*, LED*, Modified LED* and Advanced LED-AS) in the same situation. The proposed method simulates in 22 periods and about 50 min, the amount of energy for any nodes is specified 700 units, each send and receive consumes 0.3 and 1 units, respectively. Moreover, α = 0.05 in advanced and modified LED*. Fig 7 shows the remaining energy on the node which is responsible for sensing the blood pressure. Be that as it may, in A^*, all the detected information is sent, in LED*, the sent information is dictated by LED [25], and in Modified LED^* [26], the sent information is controlled by Modified LED and finally Advanced LED-AS, the sent data are determined by Advanced LED (Algorithm 1). As appeared in Fig. 6, the Advanced LED-AS calculation devours less energy than other methods calculations since the transmission is enhanced. In fact, suggested approach saves energy about eight times

more than A* and about two times more than modified LED* and four times more than LED*.
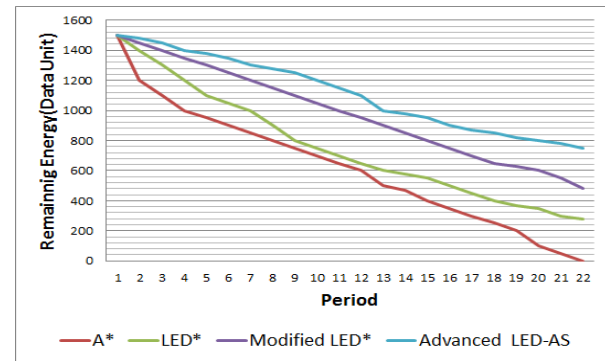

Fig. 7. Remaining energy.

C. Data Integrity

In order to check data integrity, it has been tried to simulate in 70 periods, sampling rate in maximum mode is 50 and the minimum is 10. In the following, sensed information at each period has been compared while there is not AS on the node. In this part, we compare the distribution of scores to fix data integrity. We try to estimate the confidence interval for the difference between two sets of data which sense two different scenarios, the first one is AS and another one is NS. The confidence interval for the difference between two means contains all the values of sensed data (the difference between the two population means) which would not be rejected in the two-sided hypothesis test of H0: means are equal, H1= means are not equal. If the confidence interval includes H0, we can say that there is no significant difference between the means of the two populations, at a given level of confidence.

Table 2. Data Reduction.

	Level of Risk for patient	Average difference in adaptive and non-adaptive for captured data (scores)	The Amount of data reduction
Blood pressure(watchdog sensor)	0.4	5%	80%
	0.9	3%	70%
Temperature	0.4	0.02%	90.1%
	0.9	0.02%	82.5%

According to Table 2, it can be seen that the adaptive sampling rate has not any effect on the distribution of scores. In fact, data integrity is necessary to detect the patient's health. In this simulation, we have used two features. The first one is blood pressure and another one is temperature. All periods (70 periods) temperature is normal, data never lose and data reduction has become 85.5% when the patient

situation was critical and 90.1% when patient situation was normal. On the other hand, the average difference in distribution is 0.02%.

Since the blood pressure is unstable, it is very important that in a critical situation, we do not lose important data to monitor and detect patient's health when we apply AS on the node during periods. Finally, comparing the results show that when we use the AS,

the average difference with when we do not use is about 5% during one period, while we have 80% data reduction.

In the following, in Fig 8, the amount of captured data and distribution of sensed data are provided, when we have used adaptive sampling rate and have not used adaptive sampling rate on the node of blood pressure (R=0.5, m=2).

After 70 periods, the results have proved that while we used Adaptive sampling rate, the amount of data reduces around 80% and it maintained 95% of the time

very near distributions to the original when there is not adaptive sampling rate.

Finding average difference is done by formula 8 which in that n_1 is normal populations of the first set and n_2 is normal populations of the second set. On the other hand, μ_1 is mean of the first set, μ_2 is mean of the second set, and also σ_1 is standard deviations of the first set, σ_2 is standard deviations of the second set. Finally, the amount of z is statistic.
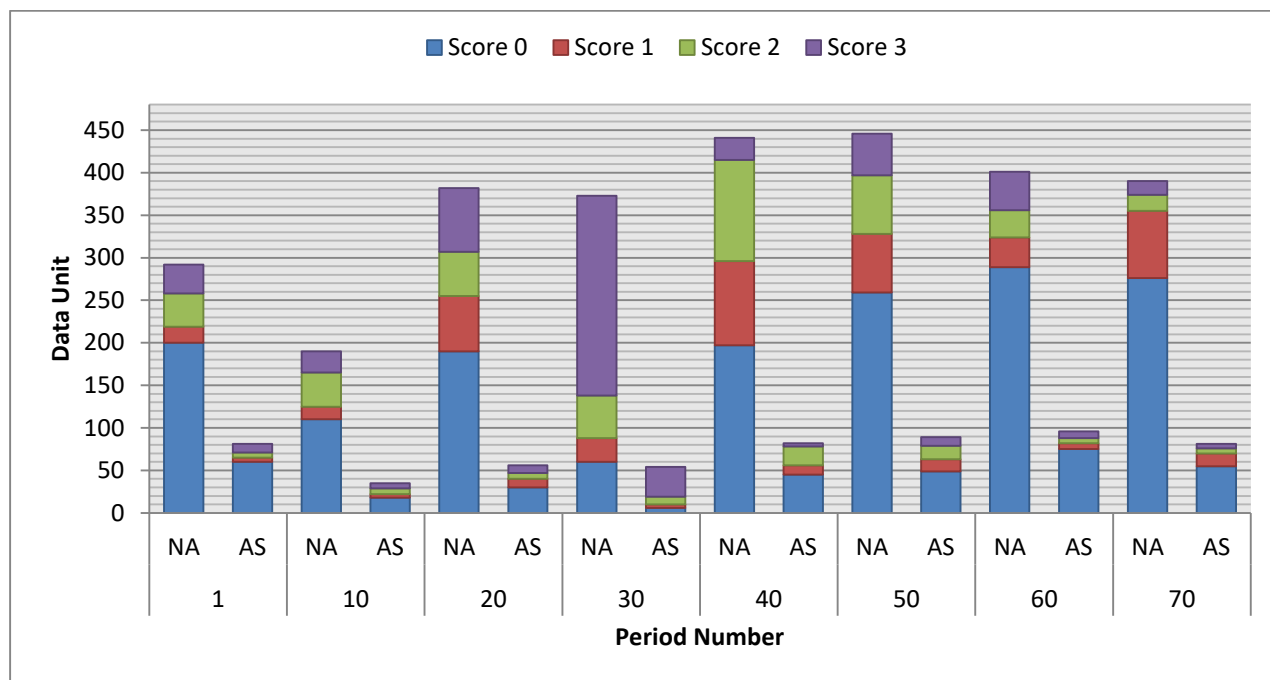

Fig. 8. Comparing number of communicated data units between adaptive sampling method and non-adaptive sampling method (NA).

$$z = \frac{(\overline{X}_1 - \overline{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \qquad (8)$$

6. CONCLUSION

In this paper, we proposed a new framework for data management and processing in Wireless Body Sensor Networks (WBSNs). In our approach, we used the context and watchdog sensor to indicate the active and sleep sensors in different time slices. Moreover, we utilized a statically test to evaluate the vital signs variance to denote an accurate sampling rate. Then we employed a suite function to calculate the best amount of sampling rate. We conducted a series of simulations on real medical data recordings to show the effectiveness of our algorithms and approaches. The results show that our approach reduces considerably the

sensed and the transmitted data and the energy consumption while maintaining data integrity. The suggestion methods cause the sampling rate to be denoted adaptively and based on the risk level of the patient. It has been tried to satisfy the energy efficiency and data reduction while keeping data integrity. Since we need enough data to estimate the patient's status, it enough data must be collected to check the patient's physiological conditions. Therefore, data integrity and providing necessary cares are performed rapidly.

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