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A Comparative Study for Evaluating Recent Advances in Wireless Body Sensor Network

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***Abstract*—Internet of things (IoT) network helps communities, cities and industries better manage their work efficiently and provides a superior quality of service. This can be applied on Wireless Body Sensor Networks (WBSN) employed in health-care industry. As any network, WBSN has its challenges that attracts researchers for its potential in serving humanity. Thus, enhancing WBSN could take many forms like enhancing the energy consumption of sensors, the communication or transmission and data analysis. Many researches cater to the above topics individually or combined to promise better outcomes. In this paper, we present a comparative study for some of the techniques and enhancement that researchers bring into WBSN for e-health applications and highlighting the gaps that would be a target for future researches. We provide a detailed overview of WBSN purposes and used techniques. The paper presents a number of the recent advanced techniques which fall under the survey's objective and compare them. For an objective comparison, we focus on a set of criteria related to e-health and involving data reduction, energy conservation, decision-making up to the intervention.**

***Index Terms*—Discovered Pattern, Disease Prediction, Energy Consumption Optimization, IoT, Network Lifetime, Wireless Body Sensor Network.**

I. Introduction

Health-care systems (HCS) were under real challenge in 2020 despite the good development in technology worldwide. They showed their fragility when pandemic happened either in diagnosing the issues, identifying the symptoms, the limited bed capacity or when the medical teams were exposed to danger. On the other hand, the elderly population is projected to be 1.5 Billion by 2050 [1] which puts additional burden on the HCS or governments to manage the increase and provide performing services. This drives the need for better data, tools, networks and systems to ensure health and safety of the population such as wireless body sensor network (WBSN). WBSN is mainly used for medical and monitoring purposes at houses, day care centers or hospitals. WBSN consists of three parts: Sensors on the patient's body (mainly battery operated) measuring vital signs (VSs) and motion detection. Coordinator for data collection and transmission like tablets, or mobile phones communicating the data with the server. They vary in functions from pure data transmitters to some offering local data analysis. Lastly, the server which can be installed at hospital, house or on the cloud to analyze the received data from patients providing useful outcomes.

WBSN faces several challenges whether in data collection, decision making accuracy or disease diagnosis. Researchers focus on these challenges and propose enhancements. They can be categorized into three main categories: data collection at the sensor level with main objectives of data and energy reduction, decision making at the coordinator or medical team level for assessing patient's situation and thirdly, disease diagnose at the server level using classification, data mining and other techniques. The intention of this report is to give a comparison between various techniques in the field. The selection criteria taking into account recent released researches, new techniques and the topics they cover while comparing them based on energy management, data analysis and solution type.

The rest of the paper is organized as follows. Section II presents a review of advances in WBSN in the three domains and related work is presented for each one. Then, a WBSN comparative study is introduced in section III. This section put forward efficient techniques and systems dealing with patient heath monitoring. In section IV, we propose a simulation and performance evaluation for the selected techniques. Finally, the conclusion and the proposal for future research are suggested in section V.

II. Related Work

WBSNs are increasingly attracting researchers for their importance and potential for improvement, whether in hardware development, data usage or vital needs. In this section, our goal is to present few techniques under each of the identified categories: data collection, decision making and disease diagnosis.

A. Data Collection

Sensors generate and send data which have direct impact on energy consumption. Researches look after this point and propose different solutions like compressing the measured data (less data to transmit); or adapting sampling rate to reduce the data to be measured. In [2], the authors adapt the sampling rate of biosensors through individual's pattern discovery and predict activity which result in network traffic improvement by more than 80% and diminish the energy

spending by 3 times. Authors in [3] propose a local emergency detection and adaptive sampling algorithm (Modified LED) at the sensor side, which adapts the sampling rate according to the variation of vital signals (VS). [4] uses a novel adaptive selection technique where the changes in measured data defines the sampling ratio that reduces the data to be sent.
Other researches deal with transmission optimization. The mostly used technique is compression sensing (CS) with and without modifications. In [5], a combined compression algorithm is proposed combining lossy and lossless techniques achieving high compression ratio values. Also, to reduce the transmission, some researches worked on local emergency detection as in [6] where author presented treatment of raw data and send the results instead.

B. Decision Making

Decision making differs depending on the purpose and location. Whether it is deciding on the sampling rate of the sensor or identifying the patient's situation (critical or not), the place where the decision has to be made can be the sensor, the coordinator or the medical team. In [7], the authors developed a system that can detect life-threatening changes in the elderly by comparing the current situation/activity with ordinary daily activities. A novel cloud-based platform using digital twins for healthcare is presented in [8]. The platform provides a unified consistent interface and algorithm for data coming from physical sensors on people. which are transferred to the cloud on the spot. After analysis, the cloud will send instructions and recommendations to the monitored people like notifications or controlling commands for the medical machines.

Intervention is a very important topic for researchers and is considered complementary to any monitoring system. In [9], the authors propose a data synthesis method for multiple sensors to determine the patient's situation based on VS scores. As a result, a consistent decision is taken each time an emergency is detected. Authors in [10], present a patient to doctor (P2D) platform with contribution on sensor and coordinator level. Using a known procedure for forecasting time series data called "Prophet", the system is able to predict the next VS. The medical staff will hence have visibility on patient's upcoming situation for the next periods and allow them to prevent patient entering in a critical situation or preparing the appropriate treatment and preventative cautions.

C. Disease Diagnosing

Analyzing the received data from sensors along with other historical data leads to more accurate outcomes using high speed workstations at server level. In [11], the authors propose a live data synthesis patient monitoring system, decision making, classification and disease diagnosis. Traditional classification techniques (Kmeans, naïve bayes, decision tree) suffer from a relatively slow performance when applied with numerous amounts of data like the case in health monitoring. Overcoming this performance issue, an update on Kmeans (SKmeans) is proposed which differs by gathering patients according to their consistency status concluded from the overall score that is computed from measurements instead of using the measurements directly. Also, for every repetition, a patient is allocated to the closet centroid according to the steadiness point [11] for the complete set of measurements and this results in enormous decrease in computation time.

In [12], the authors propose a system that evaluates people's condition using a deep learning method applied with swarm intelligence technique. The sensors are grouped and assigned a group head where the latter receives the measurements from related sensors and categories them based on Bayesian network for identifying critical condition. The authors of [13] propose a multi-level healthcare knowledge system that analyzes and saves data using many of Hadoop ecosystems [14]. The diagnosis is performed at the final level by utilizing the collected data and employing business intelligence (BI) solutions. Finally, another approach consist in proposing a supervised learning system to predict heart diseases using cooperative data fusion structure [5].

III. WBSN Comparative Study

Despite the importance of all the discussed techniques and the enhancement they bring, some techniques may be more important depending on several criteria. The selection of the compared techniques is based on results for different matrices looking at energy efficiency, accuracy and data integrity. This is in addition to other factors like journal popularity, publication date and citation giving the chance to a diverse comparison within the WBSN domain. In this section, we take five of the best techniques which passed the selection rules and compare them according to different criteria such as energy management, data analysis and solution type. The five selected techniques are AREDaCoT [15], SL-based-DSS [5], CCalgo [16], SAdaptDaCo [3] and CM-CUSUM [4].

A. AREDaCoT

The authors of [15] propose an energy-efficient patient health monitoring system by reducing the amount of collected records. The adaptive rate energy-saving data collecting technique (AREDaCoT) operates with 100 seconds duration cycles. Each cycle embeds two stages. The first one removes data redundancy using improved local emergency detection (LED) and national early warning score (NEWS). Improved LED differs from normal and modified LED. To understand the difference, assume that sensing records $R = R_0 \dots R_n$ is collected over a given period of time at the sampling rate S_r. According to NEWS, each measurement is assigned a score $S_i = \{0, 1, 2, 3\}$ to form a series of scores: e.g. for the ten measurements of V, we have $Score(R) = 0, 0, 1, 1, 0, 2, 2, 0, 3, 3$. Then LED will send the following scores $1, 1, 2, 2, 3, 3$ as it detects all measurements except the zero ones, while modified LED will send $0, 1, 0, 2, 0, 3$ as it eliminates the repetitive score. The improved LED will send the sequence $0, 1, 2, 3$ where 0 is sent since it is the first measurement. The second step involves two processes:

1- evaluating the risk score based on the monitored person's risk conditions, 2- calibrating the sampling rate with different risk level ranges. After eliminating redundancy, each score is assigned a weight and then the dynamic risk (DRisk) is calculated using equation 1. This provides dynamic sampling based on the calculated dynamic sampling range and therefore the sampling rate will be adapted accordingly.

$$DRisk = \sum_{i=0}^{N} (S_i \times W_i) \tag{1}$$

where W_i represents the i^{th} weight for the i^{th} score S_i according to the NEWS and S_i represents the number of scores S_i $(i = 0, 1, 2, 3)$ that are detected from the clinical measurements.

The energy spending is decreased by more than three times compared to a static adaptive sampling rate approach (constant risk levels) and enable patient's situation evaluation. This is mainly valuable for right time intervention by medical team. Thus, it can detect the patient status while conserving the battery consumption. However, it does not involve an end-to-end solution but only focuses at the sensor level. Furthermore, the process was applied to a single source of data from one sensor and cannot be considered as heterogeneous.

B. SL-based-DSS

The author of [5] has proposed a supervised learning support system "SL-based-DSS" for predicting heart disease. The idea is to use a cooperative data synthesis structure for predicting heart issue syndromes. Since several sensors are involved, a feature (vital sign) selection process is applied to reduce redundant or inappropriate features. This is realized by the squirrel search algorithm. Lastly, for the prediction of heart disease, a modified Bayesian network (M-DBN) is suggested. This decision support system is considered a heterogeneous system as it uses data from eleven signals to predict if there is a heart disease or not. However, this research doesn't specifically consider energy expenditure but only the disease diagnosis.

Data fusion involves three steps: pre-processing, categorization and feature mining. The important step is pre-processing, in which unwanted noise is removed using a finite impulse response filter (F_n) [5].

$$F_n = \sum_{i=0}^{N} C_i R_{n-i} \tag{2}$$

where record R_n is the input, F_n is the outcome indicator and filter constant is represented by C_i (i: 0 to N). The prediction is supported by the outcome indicator when the last uses feature identification method. The system collects signals for eleven attributes generated by many different sensors that undergo data fusion. Feature selection is the next step to improve the execution of the learning system by eliminating monotonous and irrelevant records [17] using salp swarm algorithm (SSA). The set of characteristics is placed in a matrix where SSA begins with the random starting position of features which is represented as a vector. For each feature, the best position is determined by putting the decision varying records into a custom specified function and the associated records are maintained in an array. Next, the SSA updates the position of features based on their fitness evaluation. Lastly, the prediction of heart disease is performed using M-DBN. The latter defines the optimal subset of features that is fed into the prediction process. M-DBN achieves an accuracy of 95% and outperformed existing techniques such as DBN (80%), artificial neural network (85%) and conventional neural network (80%).

C. CCalgo

CCalgo is a combined compression algorithm proposed in [16]. The author's proposal is to decrease the quantity of data to be sent with an objective to optimize the maximum admissible reconstruction error. The zero-latency compression algorithm consists of lossy and lossless techniques.

The lossy technique is built on live (zero delay) differential pulse code modulation (differential-PCM) using a prognostic filter. It sets thresholds, where values that exceed them will be selected for transmission. Such a mechanism implies an acknowledgement for each transmitted data, without the need to re-transmit the lost packets. This requires the communication protocol to embed an acknowledgement mechanism. In addition, a lossless compression algorithm using exponential Golomb code that solely depends on the accuracy of the data converter (analog to digital). Exponential Golomb coding consume less power since it compresses data directly on the spot. It is based on variable-length binary codes where smaller code-words can be allocated to the mostly used symbols. On the other hand, bigger code-words can be used for the less used words achieving a relatively low average code-word length. Such encoding is delivered even without a dictionary. Assuming that (X) is an integer belonging to (P) a set of positive numbers that is divided by the Golomb code into a finite set of indices, the code-word for (X) is composed of a prefix and a suffix. The start is an index (i) represented by ones followed by a zero (for example if i=3, then encoding is 1110). The end resembles to the rightmost bits 1+X in binary conversion. In this case, the Golomb code overall size of X which is a correct integer would be:

$$N_{bit}(X) = 1 + 2. \lfloor \log_2(1 + X) \rfloor \tag{3}$$

The results show that the efficiency of the lossy technique improves when the maximum absolute error grows larger, while the lossless better perform when vital signs are observed during prolonged intervals resulting in byte size reduction of the data to be sent. However, the combination of the two proposed gives the best performance with compression percentage rates larger than 100%.

D. SAdaptDaCo

SAdaptDaCo is a structure for biosensor data management proposed in [3], ranging from data collection to decision making. The authors use the modified LED to optimise data transmission and adaptive sampling based on the analysis of variance (ANOVA) model with Fisher test. The other objective is to use the data and make accurate decisions at the coordinator level using data fusion model such as fuzzy set theory. At the end, coordinator combines the collected records and makes the right decisions from a decision matrix based on the EWS.

The use of Fisher test and ANOVA helps detecting large changes of the taken records in a specific period. In the case of high changes, the sampling rate is set to the maximum, or else it is adjusted according to the variation and the criticality of the patient. To better explain, let us consider V_T being the total variation (i.e. the sum of the variations), V_p being the variation within period and V_t the between period variation with following equation 4.

$$V_T = V_p + V_t \tag{4}$$

The decision of variance is obtained using the Fisher test:

$$F = \frac{\frac{V_t}{(P-1)}}{\frac{V_p}{(R-P)}} \tag{5}$$

Number of records is R and P is the total sum of periods. Consider $F_t = F_{1-\beta}(P-1, R-P)$ having risk β, then the choice depends on F and F_t as below:
If $F > F_t$ or $R <$ P, then the variance is high and the sampling should be at its highest rate, while if $F \leq F_t$, then the sampling rate should be adjusted according to the function. It is important to take into account the patient's situation which can be defined by a variable risk level r_0. Low and high risk values are represented by 0 and 1 respectively. Patients having a level between $0 \leq r_0 < 0.5$ are considered to be low risk patients, while those having a level between $0.5 \leq r_0 \leq 1$ are higher risk patients and should be monitored, implying a higher sampling rate. Consecutively, a behavior function is used to find the best sampling rate between the fisher result and the patient's condition stage.

The next step is at the coordinator side with the decision making process. Considering there are sensors having readings "r" to be observed. At index "i", there will be r_i record which being monitored to decide whether an abnormal event happened, or everything is normal using the data synthesis. For example, r_i is the observed record (r_1: Respiration, r_2: heart rate, etc.) and D_j be a decision (d_1: supply oxygen, d_2: don't supply oxygen). Using synthesis data processor at the coordinator with its own ruling matrix D and a vector of records $v = [v_1, v_2, \dots, v_r]$ during one period, the coordinator decides d_j in order for:

$$\sum_{i=0}^{r}(S_{ij} - v_i)^2 <= \sum_{i=0}^{r}(S_{ip} - v_i)^2 \tag{6}$$

Given that S_{ij} represents the score of decision d_j for the record r_i and so for other decisions d_p, p is ranging from 1 to m. $\sum_{i=0}^{r}(S_{ip} - v_i)^2$ indicates how nearby the real sensor measurement to the record values predicted to support ruling decision d_p. The lesser the gap between real and expected, the more accurate the decision will become.

At the end, a comparison for the amount data to be sent in every period is accomplished in conjunction with LED and modified LED (M-LED) algorithms. The system performs better when the VSs are not stable and the variations are observed. For vital signs like temperature, the LED and M-LED techniques perform similarly because the VSs are the same during the whole period, while in the case of variant VS like respiratory rate, the M-LED performs better and decrease data by 50% , which can also save the energy consumption by the same percentage. The system is considered to be heterogeneous and managed to process data from three different signals to successfully make the decision whether to supply oxygen to the patient or not.

E. CM-CUSUM

The authors of [4] proposed an adaptive data sampling algorithm based on Modified-Cumulative SUM (CUMSUM) method to shorten the data before anomaly detection. This reduces the data to be sent and the detection time. It is achieved by using deterministic adaptive sampling (to speed up the anomaly detection) followed by collaborative approach to accurately detect anomalies which provides the lowest run time. The coordinator using CUSUM calculates the required sampling rates (SR) for each sensor; when the coordinator detects a change in data variation, it adapts the SR accordingly. The collaborative approach identifies anomalies and differentiate between those indicating real emergency conditions from normal sensor errors. A link or relationship among the sensors is therefore necessary as an anomaly demonstrating a true emergency must be seen or have impact on other vital signs. Otherwise, it is estimated to be a false alert or a sensor malfunctioning. The CUSUM computes the incremental sum of the abnormalities C_t from the desired value. The desired value is the median of the values in the training stage and it is represented by γ_0 in equation 7. Considering (S_j) is the observed stream of items S $(S_0, S_1, ..., S_n)$. At the beginning, the incremental sum C_t is calibrated at 0. Then:

$$C_t = \sum_{j=1}^{t}(S_j - \gamma_0) \text{ with } t > 1 \tag{7}$$

Record which deviates from process mean is considered as a deviation. CUSUM uses two statistics C_t^+ and C_t^- to identify small deviations.

$$\begin{aligned} C_t^+ &= max[0, S_t - \gamma_0 - H + C_{t-1}^+] \\ C_t^- &= max[0, \gamma_0 - S_t - H + C_{t-1}^-] \end{aligned} \tag{8}$$

Given that H is a configurable threshold, C_t^+ increases when high deviations or varying values are detected with the distance to $(\gamma_0 + H)$ while C_t^- increment upon identifying values that are small in distance with $(\gamma_0 - H)$ for the monitored process. After detection of an error, C_t^+ and C_t^- are set back to 0. The deviation is identified sometimes after performing many iterations which needed to influence C_t. Hence, finding the precise time for occurrence of the deviation is hard. Then, When C_t is less than the detection threshold H^+ this triggers the finish of the deviation in the monitored process. However, to achieve this condition (less than threshold H), there will be many iterations since C_t is a cumulative sum and this might delay declaring the real end of deviation. To overcome this problem, a Modified-CUSUM is proposed which allows the determination of the deviation's beginning and ending time with a good precision. This is achieved by adding a counter N that is revised with every computation of C_t. In case an error is discovered at period p, its beginning is considered as $P_{error\_StartTime} = p - N + 1$. Another counter Z quickly detects the end of the error when C_t becomes stagnant or decreases, and then the present deviation is probably going to be ended. Counter Z is revised with every computation of C_t. It represents the sum of successful declines of C_t. Starting values for N and Z are always 0.

The algorithm is applied on data received from each sensor to adjust the sampling rate SR by computing the accumulative sum C_t and assigning the SR with respect to a threshold (H) dedicated for decision. In the following computation, SR will increase to more higher values when C_t comes more closer to the threshold. The Modified-CUSUM collaborative method with adaptive deterministic sampling has 35% less energy consumption and 40% lower processing time than the Modified-CUSUM method with no sampling.

F. Synthesis and classification

In this section, we have presented the selected articles that provide a good overview of WBSN research. This research aims to make a comprehensive classification for each of the five selected researches before proposing a performance evaluation in next section IV. This classification is presented in table I based on the categories and criteria detailed in the section II.

If we try to analyse and identify the key methods contributing to the efficiency of WBSNs, we can notice that *adaptive sampling* is used in different papers to contribute in energy saving. Similarly, the technique of *local emergency detection* is included in several researches under different forms, and contributes significantly to reducing the amount of data to be sent. In terms of data analysis, *data fusion* is considered a common method in WBSNs. Finally, the *supervised learning* technique has shown good effectiveness in predicting heart disease using a modified deep belief network.

G. Limitations of the studied techniques

The five compared techniques have different objectives and methods, thus they hold diverse limitations.

AREDaCoT [15] focuses on data reduction using one sensor at a time. The redundant data is eliminated and sampling rate changes based on risk level ranges. The limitation resides in defining an accurate risk levels that require narrower ranges, this also means more calibration needed with every range. Another, is the requirement for system to analyze and correlate data from different sensors for the same patient. This helps differentiating sensors failures or inaccuracies from abnormal reads which are hard to be detected in homogeneous system like AREDaCoT. SL-based-DSS [5] succeeds in predicting heart disease but has limitations in energy management as it involves several steps that are time and energy consuming. Also its scalibilty is questioned as it is requiring many sensor data to come up with an accurate predication and this compromises performance when bigger number of patients are involved and are being analysed at the same time. For CCalgo [16], the need for acknowledgement to avoid sensor re-sending successfully delivered packets require mechanism in the communication protocol that could be challenging for some type of sensors and systems. SAdaptDaCo [3] performs well in case of high variance in VSs which allows a faster and an accurate decision while performance is reduced in the presence of low variance that can be an indication for deterioration in patient's situation and can be solved by quick intervention. Modified-CUSUM [4] depends on defined decision thresholds to control the sampling rate. Thresholds in such case can suit particular decision or classification but does not for other types and this makes the system limited at a time for special use case.

IV. Performance Evaluation

For evaluation purposes, real health data from Physio-Net [18] were extracted from the Multiple Intelligent Monitoring Intensive Care (MIMIC) database. It contains the records of more than 90 intensive care patients, of which 70 can be used in our study including VSs (heart rate (HR), blood pressure (BP), respiratory rate (RESP) and oxygen saturation (OS)). As the database contains incomplete records for some periods and many directories, the data were reorganised into one file per patient containing all records. Then we applied the data to the different techniques to formulate the comparison results.

The simulation and database are used to assess the performance of the methods presented in section III, each with the set of inputs needed. We pointed out that not all techniques use the same features or records at the same time, as some are not heterogeneous or focus on different objectives. Thus, the comparison focuses on commonalities that can be measured among these techniques to give a fair overview. Among the evaluated benchmarks, data reduction and energy conservation are common measurable objectives that are well demonstrated in each research. Accuracy and integrity play an important role in keeping WBSN reliable resource. Scalability is another factor that reflects the possibility of replicating the technique for a larger number of sensors and whether it will perform the same when deployed for large number of patients and not just for a small subset. The overall results are presented in the table II.

V. Conclusion

The rapid development of sensors, demographic changes and life span are all factors for increasing the demand on WBSNs. All studies and researches are trying to improve the usage of such network. In this paper, we have given a synopsis of WBSNs and the state of the art in solving and improving the

TABLE I
CLASSIFICATION OF RECENT RESEARCHES ON WBSN ACCORDING TO DIFFERENT OBJECTIVES

		Data Collection		**Decision Making**		**Disease Diagnosing**	
Reference	***Year***	***Energy conservation***	***Heterogeneous approach***	***Patient situation***	***Intervention services***	***Classification***	***Data Mining***
AREDaCoT [15]	2020	X		X			
SL-based-DSS [5]	2020		X	X		X	X
CCalgo [16]	2017	X					
SAdaptDaCo [3]	2016	X	X		X		
Modified-CUSUM [4]	2019	X	X				X

TABLE II
PERFORMANCE EVALUATION TABLE

Criterion	**AREDaCoT [15]**	**SL-based-DSS [5]**	**CCalgo [16]**	**SAdaptDaCo [3]**	**Modified-CUSUM [4]**
Data reduction	78%	0%	99%	71%	67%
Energy saving	62%	0%	90%	84%	65%
Integrity	100%	98%	50%	70%	92%
Accuracy	90%	95%	91%	87%	93%
Scalability	85%	70%	92%	90%	73%
Efficiency	93%	92%	100%	85%	82%

different pillars of this domain. The different referenced papers have been classified into three categories in order to provide the reader with an overview of the current research objectives of WBSNs. Among the different articles, we have selected five as representative of the field. After presenting the principles, we propose a comparison and performance evaluation of them according to different criteria.

The explored researches and the state of the art show the different research focuses within the WBSN. Most of them consider individual research focus and not an end-to-end solution that goes from energy management, disease diagnosis, decision making to intervention. We observe also that very few of them focus on disease diagnosis and decision making through a heterogeneous approach (using different VSs) which could result in more accurate diagnose of patient's conditions and thus improve decision making. Hence and the current health crisis demonstrates it, WBSNs still offer research opportunities to improve this type of networks in order to use them more effectively and disseminate more widely to counter current and future health and social crises.

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