Quality of Information for Wireless Body Area Networks

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Abstract. The Wireless Body Area Networks (WBANs) are a specific group of Wireless Sensor Networks (WSNs) that are used to establish patient monitoring systems which facilitate remote sensing of patients over a long period of time. In this type of system, there is possibility that the information accessible to the health expert at the end point may divert from the original information generated. In some cases, these variations may cause an expert to make a diverse decision from what would have been made specified to the original data. The proposed work contributes toward overcoming this foremost difficulty by defining a quality of information (QoI) metric that helps to preserve the required information. In this paper, we analytically model the QoI as reliability of data generation and reliability of data transfer in WBAN.

Keywords: Body sensor networks · QoI · Relaibility

1 Introduction

The Wireless Body Area Network (WBAN) is a specific type of a network that is designed to connect diverse medical sensors and devices, placed within and outer surface of the human body. The WBAN plays a significant role in ubiquitous communication [1]. A WBAN system uses transportable monitoring devices so it helps to provide mobility of patients [9]. The WBAN system is comprised of one or more sensors which calculate particular data of the patient, like body temperature, blood pressure or heart rate. This data is then sent toward the base station. The communication involving sensor and Mobile Base Unit (MBU) can be over a wire or wireless [1]. In health care domain, from the demography of World Health Organization, there are millions of people who undergo chronic diseases every day. Although, old age people are majorally involved, consequently for such situations WBAN creates its potential to provide instant health monitoring and medical care to the patients.

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It facilitates remote monitoring of patients. In such type of network there is possibility that the information accessible to health practitioners on end point may vary from the original information that may cause health practitioner to take a different decision for diagnosis from what would have been made using the original data [10]. There are many other optimization problems in wireless health research which creates difficultly to maintain a good quality of data. The Quality of Information (QoI) is the quality identified by the user concerning to the expected information, which completely accomplish the user evolvable constraints and reducing important resources such as bandwidth and energy [4]. The QoI is the collective effect of the available knowledge on information derived from the sensor that determines the degree of precision and confidence that those aspects of the real world (that are of interest to the user) can be represented by this information.

In the WBAN, the patient mobility results in dynamic characteristics of radio propagation. Consequently, the propagation can vary due to absorption, reflection and diffraction of electromagnetic waves around the human body. These variations have significant impact on the channel characteristics and loss of information. Apart from this, latency, accuracy and physical attributes of body sensor network also inherit the information quality.

Some difficulties are also related to the process of data transformation (i.e. wrong manipulation, input errors), and technology (i.e. equipment, body sensors). The technical trade-offs are even not adequate enough so it is necessary to take quality of information into account. There is a need of information measure which can provide the best possible information. To overcome this extensive problem there is a need of quality aware metric, and the appropriate metric was not available to monitor the quality of information. This work approaches to design a quality aware metric for information. The specific contributions of the proposed work are (1) to provide a QoI metric for WBANs, (2) propose a hypothetical model for data quality, and (3) probabilistic model for reliable and timely data transfer.

The remaining paper is composed as follows. The Sect. 2 details the existing work related to the quality of information. The Sect. 3 presents the system model and the approach that is used for designing the quality of information metric. In Sect. 4, the paper describes the analytical evaluation and data modeling of required parameters. Finally, Sect. 5 concludes and suggests for future implementations.

2 Related Work

WBAN is an emerging technology which provides uninterrupted, long-lasting and far-away monitoring of physiological information for diverse medical applications. For the cause of unreliable computation, storage space, and communication abilities of various components in the WBANs, there is a chance that the information reached to the medical health expert present at the remote location may diverge from the original. Therefore, it is necessary to ensure a good

QoI while designing any WBAN application. There also exist many information attributes, that are relevant and useful for QoI in wireless sensors. There also exists an information model in defining information attributes, which benefits to define the existing attributes [6]. To plan an application and use it in an operational perspective, one needs to give more importance on various attributes concerning QoI [6].

The work in [12] presents a framework layer for QoI, focused on the estimation of sensor network operation. This framework layer allocates decomposition of implementation with delaminating that permits the construction of an affluent instrument, required for collecting QoI. The usefulness and the brutality of this work confide in the QoI available with significance of probability based attributes. Another QoI framework for analysis of sensor network is extended in [11] with the subsequent contributions of a smart iterative procedure with a study of preventive activities and the derivation of the estimates to the performance of the system and relative performance of a range of fusion architectures that can accommodate faulty sensor operations. There is also a link between attributes of QoI rapidity and self-assurance and the equipped distinctiveness of sensor systems and events that they sense. The author in [2] shows that when remote sensing data is promoted and the raw data is altered into the valuable data, the information quality for remote sensing data attributes influences QoI attributes to highest level (like speed, accuracy and consistency). Whereas, the work in [3], defines the quality of life-critical information based on traffic load, communication nature and bandwidth occupancy that cause congestion and result in degrading network performance and information quality. Electrocardiogram (ECG), i.e., very commonly monitored health parameter is very sensitive to various types of noise sources. In [8] paper, author targets the quality enhancement of ECG signal by describing a ECG quality index utilizing signal representation with modulation spectral.

This proposed work has developed a new QoI metric for data and information quality of three health parameters while considering the two important information attributes. It is very important for transfer of medical information to be transmitted with good quality. The medical information i.e. related to human health and life. Therefore it needs to be transmitted without any error. The proposed work contributes in solution toward error free transmission.

3 Approach for QoI Metric

3.1 System Design

The BAN system is consists of various physiological sensors such as ECG, SpO2 (Pulse Oximeter Oxygen Saturation), blood pressure, heart rate and body temperature etc. The data from physiological sensors is collected at information abstraction layer where the data is set to implementation details of particular functionality then it goes for data modeling where the modeling of parameters is performed. The quality of information will be assessed by a different analysis process of timeliness and reliability as shown in Fig. 1.

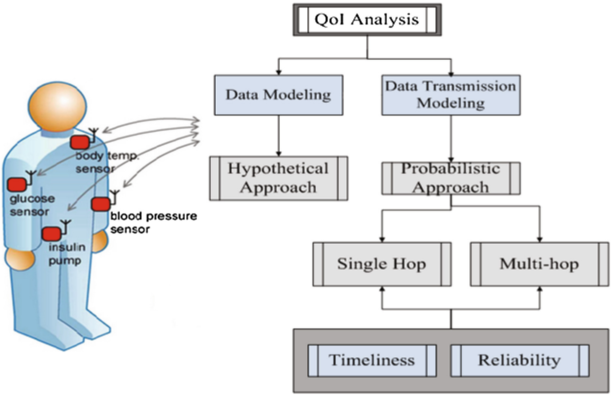

Fig. 1. Sensor network scheme

3.2 Probabilistic Approach for Quality of Information (QoI)

Hypothesis Testing. The hypothesis testing is based on the time premise recognition. The two hypothesis are based on information acquisition (i.e., hypothesis 'H1') or non availability (i.e., hypothesis 'H0').

$$H1 : r_i = s_i + n_i; \quad i = 1, ..., N \tag{1}$$

$$H0 : r_i = n_i; \quad i = 1, ..., N \tag{2}$$

In the hypothesis '*H1*', 's_i' symbolizes the value of the signal at the i^{th} instance of sampling, while in both hypothesis, 'n_i' signifies an extra noise factor which is supplementary to the i^{th} sample, and 'r_i' represents the i^{th} dimension.

Bayesian Hypothesis. Bayes theorem provides the relationship between P(A) and P(B), and the uncertain probabilities given by, $P(A|B)$ and $P(B|A)$.

$$P(A|B) = \frac{P(B|A)}{P(B)}. \tag{3}$$

The significance of above statement is based on the probability analysis of these terms, i.e., $P(A)$ is prior and is confidence degree for 'A', $P(A|B)$ is posterior and confidence degree for 'B', and $P(B|A)/P(B)$ represents the support 'B' provided for 'A'.

Assuming a null hypothesis (H0) and an alternative hypothesis (H1), where the P(H0) and P(H1) are the prior probabilities. The likelihoods are specified by $P(y|H0)$ and $P(y|H1)$, accordingly, $P(H1|y)$ and $P(H0|y)$ are given as.

$$P(H1|y) = \frac{P(y|H1)P(H1)}{P(y|H1)P(H1) + P(y|H0)P(H0)} \tag{4}$$

$$P(H0|y) = 1 - P(H1|y). \tag{5}$$

3.3 Reliability and Timeliness for QoI

The Reliability Block Diagram (RBD) provides a good relationship between WBAN data transport protocol parameters and reliability [7]. The RBD can be used to measure and assess the reliability of information transfer along erroneous channels. We assume that other operations on information are trustworthy and focus on the data transport. The proposed work verifies the operations using logs to evaluate the reliability of accessible data transport protocols by extending corresponding RBDs [5]. For reliable end-to-end (e2e) data delivery, the missing data can be recovered using corresponding Message Loss Detection (MLD) technique and can be retransmitted again. The complete data transport does not end, if the retransmission is failed. Thus, this effect is described as parallel RBD blocks for e2e data delivery. Mathematically, it can be written as

$$R = 1 - ((1 - R_R) * (1 - (R_R * R_{MLD}))^r). \tag{6}$$

where R_R is the routing reliability and R_{MLD} the reliability of MLD. R_R and R_{MLD} vary with respect to the protocols, the network conditions and the WBAN environment where it is deployed.

4 Analytical Evaluation

4.1 Data Modeling of Required Parameters

This research focuses to capture three vital sign parameters i.e. Body Temperature, Blood Pressure (BP) and Heart Rate. Three cases are specified for measuring and analyzing the information quality through considering proposed hypothetical testing. In this work, assumed values for both situations are $P(H1) = 0.75(i.e.75\%)$ and, $P(H0) = 0.25(i.e.25\%)$.

Case 1: For likelihoods assume $P(y|H0) = 0.8$ and $P(y|H1) = 0.2$, then using bayesian hypothesis $P(H0|y)$ will be equal to 8%. It says that the data received at end point will contain 8% noise, so designed data will contain 8% noise in addition with original data.

Case 2: Considering another case with assumed values of $P(y|H1) = 0.6$ and $P(y|H0) = 0.4$, bayesian hypothesis gives $P(H1|y)$ equal to 0.818. This results in $P(H0|y)$ of 18.2% which means additional noise in this case would be 18.2%.

Case 3: In case 3, assuming $P(y|H1) = 0.58$ and $P(y|H0) = 0.42$ gives $P(H1|y) = 0.8$ and $P(H0|y) = 20\%$. This increases noise addition to 20%.

4.2 Body Temperature

The thermal state of the body represents body temperature. It is an estimate of body ability to produce and dispose the amount of heat.

$$\eta_1 = \sum_{i=0}^{n} (It_i - It_D). \tag{7}$$

In Table 1, the body temperature calculations are given. The original data is actual body temperature, the detected noise is the amount of noise, and the designed data is the addition of original data and detected noise. Figure 2 indicate the analytical analysis of body temperature.

Table 1. Body temperature calculation with addition of noise (i.e., 8%, 18.2% and 20%.)

Time	Original Data F^0	Detected noise			Designed data F^0		
		8% Addition	18.20% Addition	20% Addition	8% Addition	18.20% Addition	20% Addition
0800	90	7.2	1.8	16.38	97.2	91.8	106.38
0900	92	7.36	1.84	16.74	99.36	93.84	108.74
1000	93	7.44	1.86	17.11	100.44	94.86	110.11
1100	95	7.6	1.9	17.29	102.6	96.9	112.29
1200	96	7.68	1.92	17.47	103.68	97.92	113.47
1300	98	7.84	1.96	17.83	105.84	99.96	115.83
1400	100	8	2	18.2	108	102	118.2
1500	101	8.08	2.02	18.38	109.08	103.02	119.38
1600	102	8.16	2.04	18.56	110.16	104.04	120.56
1700	104	8.32	2.08	18.92	112.32	106.08	122.92

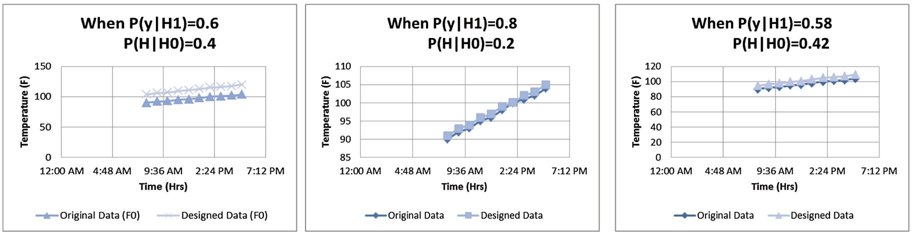

Fig. 2. Analytical analysis of body temperature with (a) 8% noise (b) 18.2% noise (c) 20% noise

4.3 Blood Pressure

The pressure applied by the blood against walls of the blood vessels is called blood pressure (BP). It is fundamental physiological parameter for human beings. The BP differs between systolic pressure (maximum, η_1) and diastolic pressure (minimum, η_2) during each heartbeat. Mathematically it is written as.

$$\eta_1 = \sum_{i=0}^{n} (Is_i - Is_D). \tag{8}$$

$$\eta_2 = \sum_{i=0}^{n}(Id_i - Id_D). \tag{9}$$

where Is_i and Id_i are ideal systolic and diastolic BP readings. Whereas, Is_D and Id_D are designed BP readings. In Table 2, BP readings at definite time intervals are given. The noise is calculated as difference between the original and designed data (Fig. 3).

Table 2. Blood pressure calculation with addition of noise (i.e. 8%, 18.2% and 20%)

Time	BP mmHg		NOISE						BP designed data					
	Original data		Systolic added noise %			Diastolic added noise %			Systolic added noise %			Diastolic added noise %		
	Systolic	Diastolic	8	18.20	20	8	18.20	20	8	18.20	20	8	18.20	20
0800	110	60	8.8	20.02	2.2	4.8	11.1	1.2	118.8	130.02	112.2	64.8	71.1	61.2
0900	120	70	9.6	21.84	2.2	5.6	12.95	1.4	129.6	141.84	122.2	75.6	82.95	71.4
1000	120	60	9.6	21.84	2.2	4.8	11.1	1.2	129.6	141.84	122.2	64.8	71.1	61.2
1100	120	70	9.6	21.84	2.2	5.6	12.95	1.4	129.6	141.84	122.2	75.6	82.95	71.4
1200	130	70	10.4	23.92	2.6	5.6	12.95	1.4	143	153.92	132.6	68	82.95	71.4
1300	130	80	10.4	23.92	2.6	6.4	14.56	1.6	143	153.92	132.6	88	94.56	81.6
1400	135	85	10.8	24.57	2.7	6.8	15.57	1.7	148.5	159.57	137.7	69	100.57	86.7
1500	140	90	11.2	25.9	2.8	7.2	16.38	1.8	154	165.9	142.8	99	106.38	91.8
1600	130	85	10.4	23.92	2.6	6.8	15.57	1.7	143	153.92	132.6	70	100.57	86.7
1700	140	70	11.2	25.48	2.8	5.6	12.95	1.4	154	165.48	142.8	77	82.95	71.4

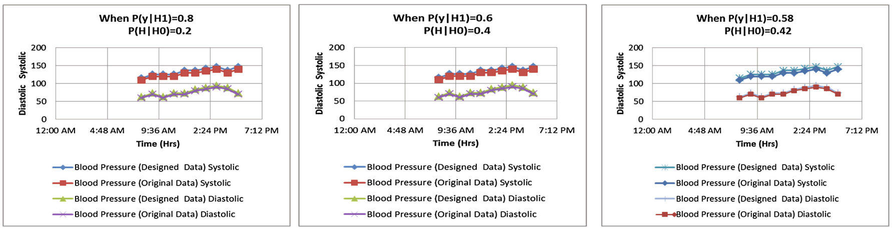

Fig. 3. Analytical analysis of blood pressure with (a) 8% noise (b) 18.2% noise (c) 20% noise

4.4 Heart Rate

The total number of heart beats per unit of time is called as heart rate. It is usually stated as beats per minute (bpm). Mathematically heart beat is given as.

$$\eta = \sum_{i=0}^{n}(Hr_i - Hr_D).k2 \tag{10}$$

where Hr_i is ideal heart rate value and Hr_D is designed heart rate value. The Table 3 depicts original data and designed data obtained by addition of 8%, 18.2% and 20% noise respectively (Fig. 4).

Table 3. Heart beat calculation with addition of noise (i.e., 8%, 18.2% and 20%)

Time	Original	Detected noise			Designed data (bpm)		
	Data (bpm)	8% Addition	18.20% Addition	20% Addition	8% Addition	18.20% Addition	20% Addition
0800	68	10.47	1.36	5.4	78.47	69.3	73.4
0900	65	10.01	1.3	5.2	75.01	66.3	70.2
1000	68	10.47	1.36	5.4	78.47	69.36	73.4
1100	68	10.47	1.36	5.4	78.47	69.36	73.4
1200	71	10.93	1.42	5.6	81.93	72.42	76.6
1300	71	10.93	1.42	5.6	81.93	72.42	76.6
1400	68	10.47	1.36	5.4	78.47	69.36	73.4
1500	73	11.24	1.46	5.8	84.24	74.46	78.8
1600	72	11.088	1.44	5.7	83.088	73.44	77.7
1700	72	11.088	1.44	5.7	83.088	73.44	77.7

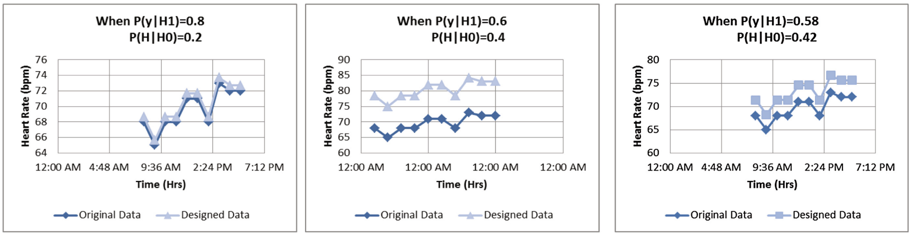

Fig. 4. Analytical analysis of heart rate with (a) 8% noise (b) 18.2% noise (c) 20% noise

4.5 Different Channel Characteristics

For required data reliability and timeliness, the different channel characteristics provide the required number of retransmissions. Therefore, we consider a case for single and multihop WBAN network with timeliness.

Single Hop with Timeliness. Using RBD techniques as discussed in Sect. 3.3, the reliability keeping timeliness requirement is calculated as,

$$R1 = (1 - (1 - H_r)) * (1 - (H_r * MLD * T))^r \quad (11)$$

where H_r is the hop reliability, MLD is message loss detection and T is the time required to transmit the data over the hop (Fig. 5(a)). From Fig. 5(b) it is evident that generally re-transmissions help in achieving reliability.

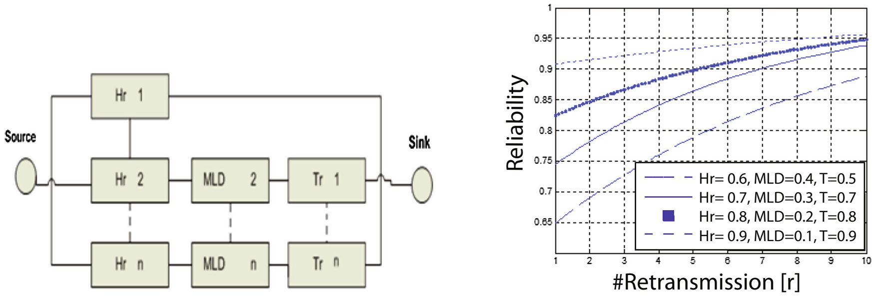

Fig. 5. WBAN single hop data transmission with timeliness; (a) RBD model, (b) analysis

Multiple Hops with Timeliness. The RBD representation of multihop transmission in WBAN with timeliness is given in Fig. 6(a) and mathematically is given as follows.

$$R1 = (1 - (1 - H_r)) * ((1 - (H_r * MLD * T))^r)^n. \tag{12}$$

Figure 6(b) depicts that allowing three retransmissions per hop reasonable reliability is achieved only for 2–3 hops (which is the case for WBAN). As the number of hops increase the reliability is decreased generally.

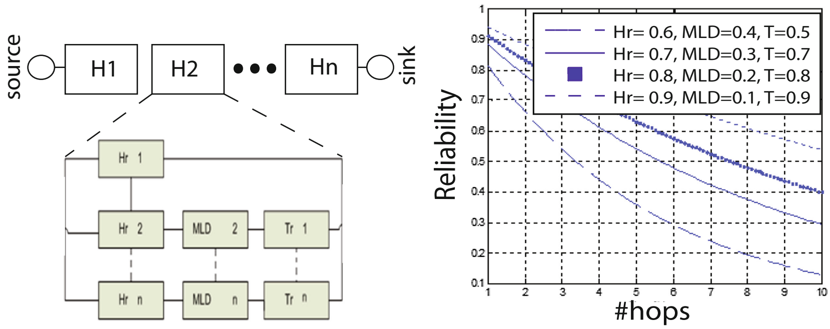

Fig. 6. WBAN multihop data transmission with timeliness; (a) RBD model, (b) analysis

5 Conclusion and Future Work

In WBAN better quality of information helps the health practitioner to make accurate diagnosis. This paper develops a new QoI metric by considering hypothetical erroneous data analysis, data delivery reliability and timeliness. The proposed QoI metric is helpful in making correct health decisions. Future work will consider more vital sign parameters like (ECG, Spo2 etc.). The future QoI metrics will include more attributes to easily obtain best information quality which will be free from all skeptics.

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