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Fault Diagnosis in Body Sensor Networks

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Abstract: **Intermittent and transient faults are the largest source of failure for body sensor networks. In order to provide a method for detecting permanent, intermittent and transient faults, a distributed online solution is suggested. The diagnosis algorithm uses repeated testing in discrete time, and diagnostic messages are sent as the output of the routine tasks of the network. This work adopts a multi-tier telemedicine system where a star topology with the sensor nodes sending their data to Personal Digital Assistant (PDA) for data fusion is used. The system performs real-time analysis of sensor data and can generate warnings regarding an occurrence of fault, which allows fault isolation and system reconfiguration.**

Keywords: Online fault detection, BSNs, intermittent fault, transient fault.

I. Introduction

Recent technological advances in sensors have enabled the design of low cost, lightweight, and intelligent physiological sensor nodes. Human body monitoring using a network of wireless sensors may be achieved by attaching these sensors to the body surface as well as implanting them into tissues. These nodes integrated into wireless body sensor networks (BSNs) are capable of sensing and communicating vital signs for health monitoring. These networks promise real-time monitoring of medical records. Though a number of ongoing research efforts are focusing on various technical issues like sensor design, routing, security and energy but there has been little work on fault detection and recovery. The sensors are mostly micro-electro-mechanical systems and can have different type of faults. The erroneous outputs from these faulty sensors might result in wrong interpretation or undesirable alarms, which may lead to life-threatening events to occur.

Fault detection and recovery for BSNs present a number of unique challenges. For a BSN, both hard and soft failures need to be addressed by considering the presence of intermittent, transient and permanent abnormalities, and the possibility of multiple and correlated failures. The hard failure includes node failures due to faulty sensors, loss of wireless communication or depleted battery. The soft failure is caused by excessive noise artifact due to poor sensor contact and/or malfunctioning of the sensor node components.

The basic principle of fault localization and analysis has been addressed by the fault tolerance computing communities for many years. However, These traditional threshold tests based distributed fault detection approaches [1–4] may not be suitable for BSNs since fault detection in BSNs is compounded by the complexity of heterogeneous sensing environment. For instance, motion sensors show different readings than ECG sensors and comparing energy of each sensor to detect the faulty node may or may not be correct. To work with traditional wireless sensor network fault detection schemes redundant sensors must be deployed. However, deploying a greater number of sensors may not be comfortable and interference between the greater group of the sensor nodes need to be addressed.

In real systems, more than 80% of the faults are intermittent faults [5, 6]. Intermittent faults are the special case of transient fault where they originate from inside the system when software or hardware is faulty. After their first appearance, they usually exhibit a relatively high occurrence rate and, eventually, tend to become permanent. On the other hand, transient faults caused by external agents like electromagnetic radiation, heat, etc. and normally, their adverse effects rapidly disappear. Since most malfunctions derive from transient faults, if they do not occur too frequently, removing the affected sensor nodes would not be the best solution for most systems [7]. By its nature, intermittent and transient faults will not occur consistently, which makes its diagnosis a probabilistic event over time [8].

The problem of transient and intermittent fault diagnosis in BSNs has been largely overlooked. This paper attempts to fill this research gap by developing a complete fault diagnosis frame work which is shown to be robust in detecting permanent, intermittent and transient faults. Since the effect of fault is not always present, detection of intermittent and transient faults require repetitive testing at a discrete time contrary to single test for permanent fault. Permanent faults are the ones that are continuous and stable in time and produce errors when they are fully exercised. Thus, issues like number of test required and time interval between two tests (T) are vital. The likelihood of detecting an intermittent and transient fault is influenced by T. If T is too large, then probability of coincident errors within the same round increases, and diagnostic latency is expected to be more. If the round length is too small, subsequently frequent sensing of data is required, which increases the energy overhead. Further, the human body environment requires a different type and frequency of monitoring. Thus proper tuning of T is indispensable, which is what this work tries to achieve.

These issues motivate to explore a generic fault detection and isolation framework for BSNs. In this work, data fusion techniques have been applied to detect faulty sensors. For instance, although being of heterogeneous nature, both the ECG and hemodynamic signals, such as blood pressure, has information mutually correlated due to the physiological interrelation of the mechanical and electrical functions of the heart [9]. This existing interconnection has been exploited in this work for fault detection. This work is an extension of our earlier work [10].

The remainder of the paper is organized as follows: Section II presents related works. Section III presents system model. Detection algorithm is investigated in Section IV. The performance of the proposed algorithm is presented in Section V and finally conclusions and future work is given in Section VI.

II. Related Work

Fault detection and fault tolerance in wireless sensor networks have been studied for many years [2, 11–14]. The existing fault detection schemes for wireless sensor networks work with the assumption that sensors from the same region should have recorded similar sensor reading. These approaches exploit the fact that sensor faults are likely to be stochastically unrelated, while sensor measurements are likely to be spatially correlated. This approaches may not be applicable in BSNs for reasons stated earlier such as: (a) BSN constitutes of heterogeneous sensors that produce different data; and (b) it is impractical to use redundant sensors for the same purpose. The performance of wireless body sensor based mesh network for health application is presented by Benjamin1 and Sankaranarayanan in [24].

In [15], an adaptive and flexible fault-tolerant communication scheme for BSNs, namely AFTCS, is proposed. AFTCS adopts a channel bandwidth reservation strategy to provide reliable data transmission when channel impairment occurs. However, this paper does not discuss effects of node failure on reliable data communication.

The issue of Identification and isolation of a faulty motion sensor node based on the data collected in body sensor networks is presented by Kim *et al.* [16,17]. In this approach the sensor readings of nine different locations are grouped with six manually segmented motion groups by considering the fact that some set of nodes on a particular motion shares similar characteristic. This approach explores this fact by implementing a history-based and non-history based fault detection using the Active Correlation Set (ACS) that dynamically or statically binds the neighboring nodes for lookup reference of node signal comparisons. Here, a sliding window technique is used to the segment sensor data stream to capture the motion characteristics and transform each segmented signal into the proper data format. Singular Value Decomposition (SVD), Power Spectral Density (PSD) and Relative Positional are used to obtain this data format.

Zappi *et al.* [18] have investigated the use of sensor fusion techniques for gesture recognition. They have investigated the outcomes of classifier fusion in function of the number of sensors on the recognition performance, and on the robustness to faults. They have advocated that sensor fusion implicitly allows compensating for typical faults up to high fault rates.

In [19], a self-healing framework for BSNs is presented, which enables a flexible choice of components for detection and masking of faults as well as reconfiguration of the network. The authors have focused on activity recognition with sensor information fusion to determine patterns of fault management. They have investigated the impact of errors such as those arising from noise or drift in sensor readings.

In summary, existing fault detection schemes for BSNs work with the assumption that sensors are either permanent faulty or fault free. This assumption may not be true in real time applications since in real systems, more than 80% of the faults are intermittent or transient faults. This paper presents a generic detection scheme which takes care of permanent, intermittent and transient faults in BSNs.

III. System Model

A. BSN Architecture

Figure III presents multi tire architecture for BSN. Tier one includes a number of on-body wireless medical sensor nodes. Each sensor node can sense, sample, and process one or more physiological signals. For example, an electrocardiogram sensor (ECG) can be used for monitoring heart activity, a blood pressure sensor for monitoring blood pressure, a tilt sensor for monitoring trunk position, and motion sensors can be used to discriminate and estimate the level of activity. Tier two encompasses a Personal Digital Assistant (PDA), a cell phone, or a home personal computer. The PDA is responsible for providing an interface to the wireless medical sensors, an interface to the user, and an interface to the medical server. PDA is also responsible to locate faulty or malfunctioning sensors. Tier three includes a medical server(s) accessed via the Internet.

B. Fault model

The proposed model considers both hard and soft faults [1]. If a node is hard faulty, the sensor node is unable to communicate with PDA. A soft faulty node continues to operate and communicate with altered behavior. Both the hard and soft faults may occur intermittently. As suggested by Breuer [20], in this work the statistics of the intermittent and transient fault is modeled by two-state Markov chain.

C. Diagnosis Terminology

Definition III.1 *Online diagnosis is the ability to execute diagnostic tests without interrupting system operation.*

Definition III.2 *A diagnosis is said to be a complete, if within a bounded time the actual fault set can be identified. A diagnosis is said to be a correct, if no fault-free nodes are*

[1] Faults are classified as: crash, omission, timing, and Byzantine. Crash faults are hard faults, and all the others can be treated as soft faults.

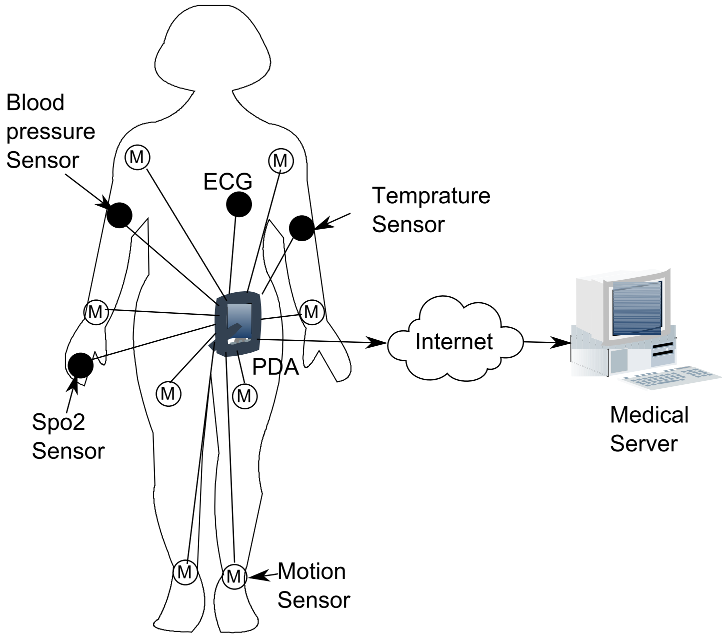


Figure. 1: Multi-tire architecture for BSNs

identified as faulty and no faulty nodes are identified as fault-free.

IV. The Detection Algorithm

This section introduces an online detection algorithm for BSNs. One advantage of the proposed work is that diagnosis is not considered as an offline but as an online core fault tolerant mechanism fully integrated in the BSN fault tolerant strategy. It uses error detection information derived from mutually correlated information from multiple sensors. This work tries to minimize the overhead in executing the diagnosis algorithm.

A. Permanent Fault Detection Algorithm

This algorithm assumes that only permanent fault exists in the network. However, this assumption is relaxed in the subsequent sections. For BSNs, the nature of faults can be attributed to a number of sources like motion artifacts, inherent limitations and possible malfunctions of the sensors. In practice, it is desirable to rely on sensors with redundant or complementary data to maximize the information content and reduce errors [21]. This is achieved through multi-sensor fusion, which is concerned with the use of multiple sources of information. This work explores the multi-sensor fusion technique in detecting faulty sensors in the network. Figure 2 shows the flow diagram of fault detection through sensor fusion. In this process, PDA collects information from all sensors at each communication round. The required features are extracted from each of the signals received and then associated. At feature level fusion stage PDA takes a decision about each sensor and detects them either faulty or fault free. For example, in cardiac sensing both ECG and hemodynamic signals, such as the impedance cardiograph or blood pressure has mutually correlated information about the heart due to the physiological coupling of the mechanical and electrical functions. In situations where the ECG signal is degraded

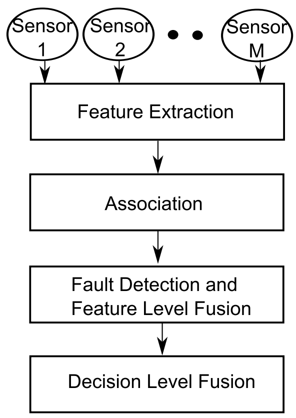


Figure. 2:

and signals from additional sensors such as the ventricular pressure is well in its range then a decision can be taken, and the ECG sensor detected as soft faulty. Table 1 shows the correlation between heart rate and blood pressure for different heart conditions. Similarly, this work explores the cor-

Table 1: Correlation between Heart Rate and Blood Pressure [22]

Patient Condition	Blood Pressure (mmHg)	Heart Rate (BPM)
Healthy Heart	120/80	75
Weak Pulse	110/80	95
Tachycardia	120/105	130
Bradycardia	120/60	45

relation of ECG signal and SPO2 signal for sensor fault detection. From expert clinical observation, if the heart rate is $70-72$ per minute, then cardiac output would be 5 liters per minute where cardiac output is the amount of blood ejected from the heart. This increases during the exercises. Considering normal beats, i.e. 72 beats/min the saturation of oxygen in the arterial blood (SPO2) is 100%. Now, we can determine SPO2 as follows

$$SPO2 = \text{Heart rate} \times \frac{100}{\text{cardiac output}} \tag{1}$$

The maximum heart rate and cardiac output vary according to the age and sex. This work calculates these parameters as follows. From [23] the maximum heart rate can be calculated as

$$HR_{max} = 205.8 - (0.685 \times age). \tag{2}$$

The cardiac output can be calculated as

$$Q = 2ml \times \text{Pulse Pressure} \times \text{Heart rate} \tag{3}$$

where pulse pressure is the difference between the systolic and the diastolic pressures. In the situation where the ECG sensor reading and blood pressure sensor reading is well within range and SPO2 reading deviates then SPO2 sensor is detected as soft faulty. This work suggests the use of redundant temperature sensors for fault detection since the cost and size of such sensors are less compared to other on body sensors.

Faults in motion sensors can be identified by considering a maximum relative distance between neighboring nodes. For instance, maximum distance from a left hand to a left shoulder is fixed that the hand cannot be stretched beyond its full length from the shoulder. Thus, it is evident that there is a fixed range of relative distances from one joint to another joint. At the time of sensor deployment the maximum Euclidean distance d_{max} between each motion sensor is recorded in PDA. Since the accelerometer is used as the motion sensor, accordingly the position of the motion sensors can be calculated as

$$pos_i = \int\int \vec{a}\, dtdt \tag{4}$$

where $\vec{a}$ is the accelerometer sensor reading vector. Using (4) the Euclidean distance between any two sensors can be calculated as

$$d_{ij} = \sqrt{pos_i^2 - pos_j^2}. \tag{5}$$

At each diagnosis, round PDA calculates the Euclidean distance between each sensor. Let's assume that there are n number of motion sensors integrated to the BSN. Let's say the syndrome $s_{ij} = 1$ if $d_{ij} > d_{max}$. Now decision can be made on status of each motion sensor as follows

$$m_i = \begin{cases} \text{Fault free} & \text{if } \sum_{j=1, i\neq j}^{n-1} s_{ij} \leq T_h \\ \text{Soft faulty} & \text{otherwise} \end{cases} \tag{6}$$

where $T_h = 0.5n$. The proposed work detects non reporting sensor as hard faulty. The node m_i cannot report to PDA due to one or more of the following reason: the transceiver of m_i is faulty, battery is drained and node is completely damaged.

B. Intermittent Fault Detection Algorithm

To test for permanent faults, any particular test need only be applied once. The only approach to test for intermittent faults is through repeated application of tests. The repetition of test is needed since the effect of such a fault is not always present. Further, presence of fault may not be observed if the duration of fault appearance is smaller than T. Thus to diagnose the network with highest accuracy in presence of intermittent fault, proper tuning of T is vital, which is what the proposed work tries to achieve.

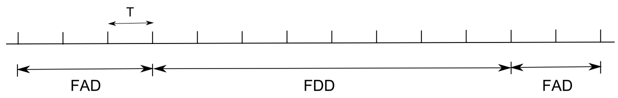


Figure. 3: Appearance and disappearance of fault

Once intermittent fault is activated in a sensor node, faults are observable for a duration FAD (fault appearance duration) before they disappear. Eventually, errors will reappear after FDD (fault disappearance duration) either because of permanent faults or correlated intermittent faults. This is depicted in Fig.3. The behavior of the intermittent fault can be characterized by measuring or estimating the probabilities of error disappearance and reappearance in discrete time $k \times T$.

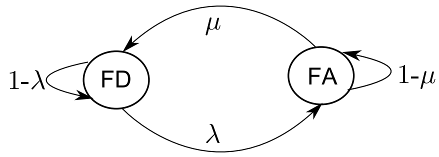


Figure. 4: Analytical model for the occurrence of intermittent fault

In order to analyze intermittent fault in more details the statistics of intermittent fault modeled as a two-state Markov model where state FA corresponds to fault appears and state FD corresponds to fault disappears. The probabilities for going from one state at T_n to either state FA or FD at time T_{n+1} depends on FDD and FAD respectively. The FAD for intermittent faults is system specific, and it depends on multiple factors such as the specific component of the sensor node being damaged or the activation patterns of the embedded software. Intermittent fault usually exhibits a relatively high occurrence rate after its first appearance and eventually tends to become permanent. Therefore, a Weibull distribution is considered for FDD with shape parameter $\beta > 1$. Without loss of generality exponential distribution is assumed for FAD with a constant failure rate $\mu = (1/\text{mean time in FA state})$.

Tuning of detection parameter T has a strong impact on the measures of interest. The longer the value of T, the higher the diagnosis latency and shorter the value of T, more the probability that first occurrence of fault is detected at the first test. Further, the human body environment requires a different type and frequency of monitoring. Thus, finding a good trade-off between latency and number of tests becomes harder. To address this trade off and make the algorithm adaptive to different type and frequency of monitoring, total health monitoring period is sampled at a rate equals to the highest frequency of monitoring. Each node in the network takes reading at these sample interval(s) and sends these reading(s) to PDA at their defined time slots. For example, heart requires frequent monitoring as compare to body temperature. Thus, the total monitoring period is sampled with a sampling rate equals to that of heart monitoring rate. Let's say SPO2 signal needs to be send to PDA at a rate three times less than that of heart monitoring rate. The SPO2 sensor node stores these data collected at three sample intervals and send these data to PDA at its time slot. Similarly, all sensors collect their data at the sample interval(s) and store them temporarily and then send them to PDA at their respective time slots. At data fusion stage, PDA compares the readings obtained at sample intervals from correlated sensors and takes decision regarding state (faulty or fault free) of each sensor.

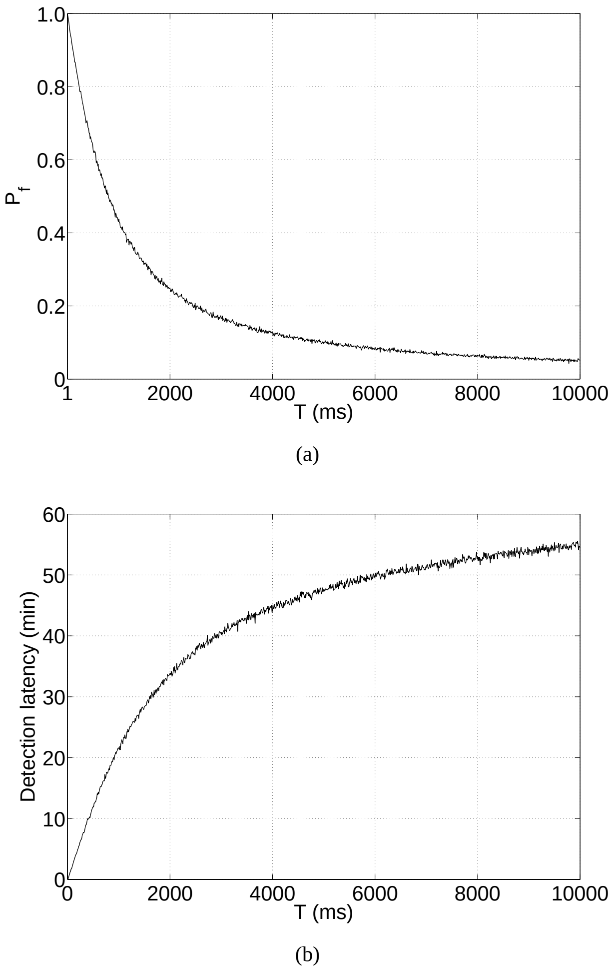


Figure. 5: Analysis of design parameter T (a) Probability that the first occurrence of faults is detected at the first test. (b) Detection latency (time to isolate faulty nodes)

Figure 5 depicts the sensitivity analysis of detection parameter T. These results are obtained for following values. The mean value of FAD for an intermittently faulty node is considered $500ms$ where FAD is exponentially distributed. The FDD is assumed to follow a Weibull distribution with increasing failure rate ($\beta = 1.5$) and expected value of $0.5\ hour$. Figure 5.(a) shows the probability (P_f) that the first occurrence of fault is detected at first test. As expected, P_f decreases with an increase in T. The average latency of isolation of faulty nodes at varying values of T is plotted in Figure 5.(b). As anticipated, increase the length of T also increases the time necessary to isolate faulty nodes. However, The latency tends to grow much less for values of T greater than $3500\ ms$.

This work advocates the value for T between $100\ ms$ to $800\ ms$. The reason is that heart requires continues monitoring, and the state of the ECG sensor must be continuously checked. Further, the probability that the first occurrence of faults is detected at the first test is high (0.7-0.95) for $T = 100 - 800\ ms$.

C. Transient Fault Detection

If a test is applied to a node and the node fails the test, then three conclusions can be drawn: the node is either permanent faulty or intermittent faulty or transient faulty. A node is detected as permanent (soft) faulty if the node fails consecutive tests. Otherwise the fault may be intermittent or transient. As discussed earlier removal of nodes with transient faults will reduce the available resources and is not cost effective. Thus, discrimination of transient from intermittent faults is crucial. This section presents a threshold based scheme that discriminate the transient from intermittent fault. As suggested in Section IV-B, tests are scheduled at the periodic time $k \cdot T(k = 1, 2, \cdots)$ for a fixed T. Once the fault appears and detected by the applied test pattern, the identified node enters to observation stage. A node in observation stage is restricted from doing any routine activities. The inter fault appearance period $T_i(i = 0, 1, 2, \cdots)$ is used to discriminate transient from intermittent fault. For intermittent faulty nodes, it is expected that $T_i + 1$ is less than T_i. In this work if $T_i + 1 < T_i$, then the algorithm increases the confidence level of being intermittent faulty (CL) by a factor 1. On the other hand, if $T_i + 1 \geq T_i$, then the algorithm reset the confidence level of being intermittent faulty to zero. The node is isolated if the confidence level crosses a predefined threshold T_{h1}. A formal description of the algorithm is in Algorithm 12.

Algorithm 1

Test are scheduled at periodic time $k \cdot T(k = 1, 2, \cdots)$ for a fixed T. Upon the first appearance of a fault the node enter to observation state.
if $T_i + 1 < T_i$ **then**
    $CL = CL + 1$
end if
if $T_i + 1 \geq T_i$ **then**
    $CL = 0$
end if
if $CL \geq T_{h1}$ **then**
    Node is intermittent faulty and is isolated.
else
    Node is transient faulty and is reintegrated in BSN.
end if

V. Performance Analysis

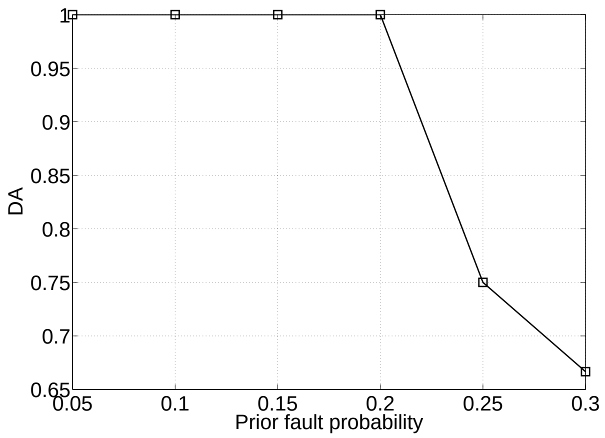
The performance of the proposed fault diagnosis algorithm is evaluated by computer simulation. In this simulation we consider one ECG sensor, one EEG sensor, three temperature sensors, one blood pressure sensor and two SPO2 sensors. Similar to [25], we considered nine motion sensors.

p	$p_t = 0.0$	$p_t = 0.05$	$p_t = 0.05$	$p_t = 0.15$	$p_t = 0.20$
0.05	1	1	1	1	1
0.1	1	1	1	1	1
0.15	1	1	1	1	0.8333
0.2	1	1	1	0.8571	0.7143
0.25	0.75	0.75	0.75	0.667	0.667
0.3	0.667	0.667	0.6364	0.5714	0.5455

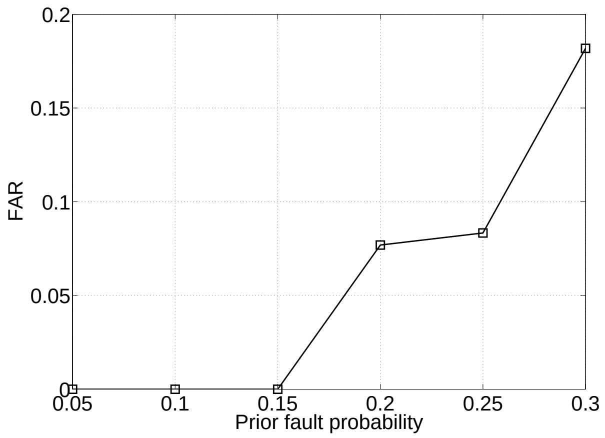
Table 2: Detection accuracy

1) Experiment 1 (assuming only permanent faults)

In this experiment we assume that all faults in BSN are permanent. For better analysis we further assume that all are soft faults as detection of hard fault is straight forward and does not require any analysis. In this simulation the sensors are randomly chosen to be faulty and the performance is analyzed by observing the detection accuracy (DA) and false alarm rate (FAR). DA is defined as the number of faulty sensor nodes detected to the total number of faulty sensor nodes in the network. FAR is defined as the ratio of number of fault free sensor nodes detected as faulty to total number of fault free nodes in the network. As depicted in Figure 6. (a), the



(a)



(b)

Figure. 6: (a) Detection accuracy. (b) False alarm rate.

detection accuracy is well maintained upto fault probability of 0.2. It is observed that the faults in motion sensors are correctly detected irrespective of fault probability. The reason is that the proposed algorithm fails in detecting the faults in motion sensors only when more than half of the motion sensors are faulty. The probability of mentioned number is very less. In addition if any one out of ECG sensor, EEG sensor, blood pressure sensor and SPO2 sensors is working then state of others can be correctly detected. It is observed from Figure 6. (b) that the FAR is manageably small. A fault-free motion sensor never detected as faulty due the same aforementioned reason. However, the non motion sensors may wrongly detected as faulty if fault probability is high.

A. Experiment 2

In this experiment the assumptions made in Experiment 1 is relaxed. We have performed simulation to estimate the performance degradation due to transient faults. For this simulation, the expected time to failure for fault-free node is taken 10 hours and the expected time to failure for intermittent faulty node is taken 1 hour. The mean value of FAD is $0.5ms$ and $T = 100ms$. As shown in Figure 7, the value for the threshold T_{h1} is experimentally found. In this experiment we chose $T_{h1} = 10$ as the detection correctness is 100% for values more than this. Table 2 and 3 shows the performance of the detection algorithm in presence of transient faults wher p_t is the transient fault probability.

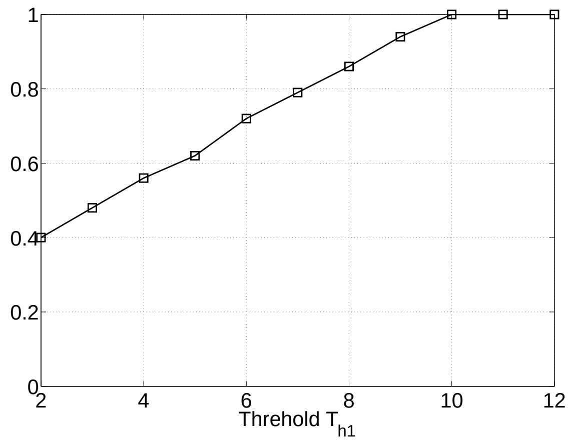


Figure. 7: Analysis for detection correctness

VI. Conclusions

Fault detection in sparse networks is relatively more challenging. As presented in present literature, detection accuracy drops with network size. In BSNs smaller number of sensor nodes are deployed for monitoring activities of daily living since wearing redundant sensors is stressful. Another challenge is to find the right neighbors for data validation in order to increase detection accuracy. In this paper, we have

p	$p_t = 0.0$	$p_t = 0.05$	$p_t = 0.05$	$p_t = 0.15$	$p_t = 0.20$
0.05	0.000	0.000	0.000	0.000	0.077
0.1	0.000	0.000	0.000	0.083	0.083
0.15	0.000	0.000	0.000	0.1538	0.1667
0.2	0.0769	0.0769	0.2308	0.2308	0.2727
0.25	0.1667	0.1667	0.2727	0.3000	0.3000
0.3	0.1818	0.1818	0.3333	0.3333	0.3750

Table 3: False alarm rate

proposed a generic detection algorithm which addresses the fundamental problem of identifying faulty (permanent, intermittent and transient) nodes in a BSN. The algorithm is simple and detects faulty sensor nodes by extracting relevant features from sensor node data. We have shown the impact of design parameter T on detection latency. A threshold based approach to discriminate transient from intermittent fault is suggested. This in turn increases the reliability.

References

[1] J. Chen, S. Kher, and A. Somani, Distributed fault detection of wireless sensor networks, in *DIWANS '06: Proceedings of the 2006 workshop on Dependability issues in wireless ad hoc networks and sensor networks*, pp. 65-72, 2006.

[2] M.-H. Lee and Y.-H. Choi, Fault detection of wireless sensor networks, *Computer Communications*, 31(14), pp. 3469 - 3475, 2008.

[3] P. Jiang, A new method for node fault detection in wireless sensor networks, *Sensors*, 9(2), pp. 1282–1294, 2009.

[4] A. Mahapatro and P. M. Khilar, Detection of node failure in wireless image sensor networks, *ISRN Sensor Networks*, 2012, pp. 1–8, 2012.

[5] R. Horst, D. Jewett, and D. Lenoski, The risk of data corruption in microprocessor-based systems, in *The Twenty-Third International Symposium on Fault-Tolerant Computing*, pp. 576 –585, 1993.

[6] D. P. Siewiorek and R. S. Swmlz, *The Theory and Practice of Reliable System Design*, Digital Equipment Corporation, 1982.

[7] A. Bondavalli, S. Chiaradonna, F. Di Giandomenico, and F. Grandoni, Threshold-based mechanisms to discriminate transient from intermittent faults, *IEEE Transaction on Computers*, 49(3), pp. 230–245, 2000.

[8] M. Barborak, A. Dahbura, and M. Malek, The consensus problem in fault-tolerant computing, *ACM Computing Survey*, 25, pp. 171–220, 1993.

[9] A. Hernandez, G. Carrault, F. Mora, L. Thoraval, G. Passariello, and J. Schleich, Multisensor fusion for atrial and ventricular activity detection in coronary care monitoring, *IEEE Transactions on Biomedical Engineering*, 46(10), pp. 1186 –1190, 1999.

[10] A. Mahapatro and P. M. Khilar, Online fault detection and recovery in body sensor networks, in *World Congress on Information and Communication Technologies (WICT)*, pp. 407 – 412, 2011.

[11] S. Chessa and P. Santi, Crash faults identification in wireless sensor networks, *Computer Communications*, 25(14), pp. 1273 - 1282, 2002.

[12] T. Clouqueur, K. Saluja, and P. Ramanathan, Fault tolerance in collaborative sensor networks for target detection, *IEEE Transactions on Computers*, 53(3), pp. 320 – 333, 2004.

[13] X. Luo, M. Dong, and Y. Huang, On distributed fault-tolerant detection in wireless sensor networks, *IEEE Transactions on Computers*, 55(1), pp. 58 – 70, 2006.

[14] A. Mahapatro and P. M. Khilar, SDDP: Scalable distributed diagnosis protocol for wireless sensor networks, in *Contemporary Computing*, pp. 69–80, 2011.

[15] G. Wu, J. Ren, F. Xia, and Z. Xu, An adaptive fault-tolerant communication scheme for body sensor networks, *Sensors*, 10(11), pp. 9590–9608, 2010.

[16] D.-J. Kim and B. Prabhakaran, Motion fault detection and isolation in body sensor networks, in *IEEE International Conference on Pervasive Computing and Communications (PerCom)*, pp. 147 –155 (2011).

[17] D.-J. Kim and B. Prabhakaran, Motion fault detection and isolation in body sensor networks, *Pervasive and Mobile Computing*, 7(6), pp. 727 – 745, 2011.

[18] P. Zappi, T. Stiefmeier, E. Farella, D. Roggen, L. Benini, and G. Troster, Activity recognition from on-body sensors by classifier fusion: sensor scalability and robustness, in *3rd International Conference on Intelligent Sensors, Sensor Networks and Information*, pp. 281 –286, 2007.

[19] T. Bourdenas and M. Sloman, Towards self-healing in wireless sensor networks, in *Sixth International Workshop on Wearable and Implantable Body Sensor Networks*, pp. 15 –20, 2009.

[20] M. Breuer, Testing for intermittent faults in digital circuits, *IEEE Transactions on Computers*, C-22(3), pp. 241 – 246, 1973.

[21] G.-Z. Yang, *Body Sensor Networks*, Springer-Verlag, 2006.

[22] R. S. Khandpur, *Handbook of Biomedical Instrumentation*, second edition, Tata McGrawHill, India, 2003.

[23] R. Robergs and R. Landwehr, The surprising history of the hrmax=220-age equation, *Journal of Exercise Physiology*, 5(2), pp. 1–10, 2002.

[24] N.A. Benjamin and S. Sankaranarayanan, Performance of wireless body sensor based mesh network for health application, *International Journal of Computer Information Systems and Industrial Management Applications*, 2, pp. 20–28, 2009.

[25] K. Sakib, Asynchronous failed sensor node detection method for sensor networks, *International Journal of Network Management*, 22(1), pp. 27–49, 2011.

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