IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-7, Issue-6, June 2019 E-ISSN: 2347-2693

Dual Sensor based Wearable Sensor Fault Detection for Reliable Medical Monitoring

D.M. Pavithra [1*], P. Ramchandar Rao [2]

[1,2] Department of ECE, SR Engineering College SR Engineering College, Warangal, India

DOI: https://doi.org/10.26438/ijcse/v7i6.11001103 | Available online at: www.ijcseonline.org

Accepted: 07/Jun/2019, Published: 30/Jun/2019

Abstract— As the medical body sensor network (BSN) is usually resource limited and vulnerable to environmental effects and malicious attacks, faulty sensor data arise inevitably which may resultin false alarms, faulty medical diagnosis, and even serious misjudgment. Thus, faulty sensor data should be detected and removed as much as possible before being utilized for medical diagnosis making. Most available works directly employed fault detection schemes developed in traditional wireless sensor network (WSN) for body sensor fault detection. However, BSNs adopt a very limited number of sensors for vital information collection, lacking the information redundancy provided by densely deployed sensor nodesin traditional WSNs. In light of this, a Dual sensor network model based sensor fault detection scheme is proposed in this project, which relies on double sensor data for establishing the conditional probability distribution of body sensor readings, rather than the redundant information collected from a large number of sensors. Furthermore, the Dual sensor network-based scheme enables us to minimize the inaccuracy rate by optimally tuning the threshold for fault detection. Extensive online dataset has been adopted to evaluate the performance of our fault detection scheme, which shows that our scheme possesses a good fault detection accuracy and allow false alarm rate.

Keywords— Arduino UNO, Health Care, Radio Frequency, W.S.N.

I. INTRODUCTION

In recent years, the medical body sensor network (BSN) has increasingly gained interests in both academia and industry. As a promising and flexible platform, the medical BSN is expected to provide continuous, important, dramatic, and timely information of patient's physical and biochemical parameters under natural status for important and critical applications, e.g., monitoring patients with hypertension or diabetes mellitus.

Medical applications have strict requirements for reliability. Faulty sensory data might result in false alarms, faulty edical diagnosis, and even serious misjudgment. As the medical BSN is usually resource-limited, e.g., energy, memory, and processing power limited, vulnerable to environmental effects and malicious attacks, faulty sensory data arise inevitably. Although the current development of wearable devices (e.g., Applewatch) greatly enhances data reliability, but even incorrect placement or sliding of the body sensor can lead to unreliable measurements. Thus, fault detection is extremely important to ensure the reliability of sensory data before the medical diagnosis-making process [2].

Sensor faults (sometimes called outliers or anomalies) are sensory readings that deviate from the normal values of physical world monitored by sensors [3]–[5]. Fault detection is one of the fundamental tasks before sensory data being utilized for conclusion-making.

Most of the available works for fault detection of WSNs are based on one assumption that there are a large number of sensors used for event monitoring, a faulty sensory reading can be detected by the redundant information collected from those sensors, which is not suitable for BSNs because of the very limited number of body sensors. Thus, it is important to take into account the temporal and spatial correlations of body sensors for fault detection of BSNs.

There are few related works for fault detection of BSNs. Mahapatro and Khilar [17], and Kim and Prabhakaran [18] used the rule-based method for simple fault detection of BSNs, which worked on a precondition that there were correlations among vital signs, e.g., from medical observation, if the heart rate is 70–72 per minute, then cardiac output would be 5 L/min, where cardiac output is the amount of blood ejected from the heart. Salem *et al.* [1] utilized linear regression to estimate the sensory reading by readings of its neighbouring sensors. A sensory reading was considered as a fault if its deviation to the estimated reading was larger than a threshold. However, human vital signs may not have quantitative correlations and it cannot decide which Reading is faulty when some fault occurs.

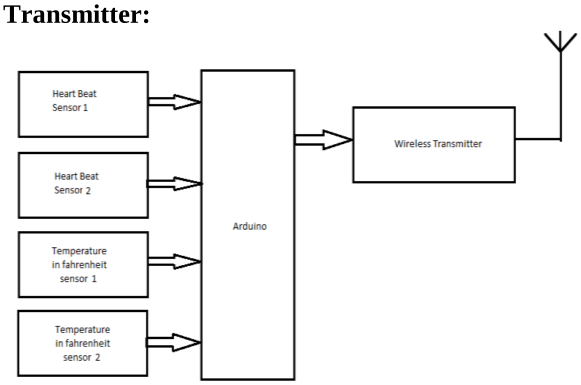
II. Related Work

Fault detection has been studied in wireless sensor networks (WSNs) for many years [7].Wu *et al.* [8] utilized a Gaussian distribution of the difference between a sensory reading and the median reading of its neighbors to detect sensor faults. Sheng *et al.* [9] formalized a histogram-based approach to detect global faults in WSNs. Palpanas *et al.* [10] provided a kernel-based method for sensor fault detection. Ramaswamy *et al.* [11], and Cover and Hart [12] proposed a nearest-neighborbased fault detection scheme for WSNs, which determined data as a fault if it was located far from its neighbors. Rajasegarar *et al.* [13] formalized a clustering-based fault detection approach for WSNs. Krishnamachari *et al.* [14] and Luo *et al.* [15] provided distributed Bayesian algorithms for fault diagnosis of event region with binary values. Annichini *et al.* [16] proposed a generic localized fault detection algorithm of majority vote to identify faulty sensory data.

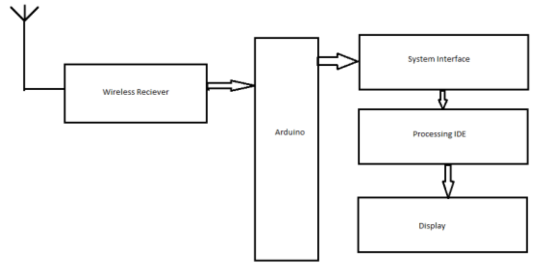
III. Methodology

Here we are using Arduino UNO for programming, in this project we are employing the two sensors for each type, like temperature sensor two in number and Heart Beat sensor two in number we are reading this sensor values continuously from the patient and storing the values in the memory and at every instant of time when we are displaying the sensor values we will compare the values of both the sensors and we will take the average of the sensor values and then we will send the final values to the care taker in the nursing home wirelessly by using 433MHz RF Modules. Patients health parameters are collected using pair of sensors and an inventory is made. When approximation values of the both sensors are equal, then there is no malfunction in sensors When there is a abnormality in the sensed values the nearest value to the stored inventory is processed and faulty sensor data is omitted and same is indicated on the console.

Block Diagram
Transmitter:



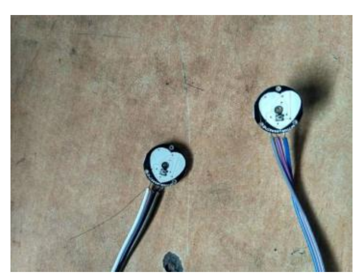
Receiver:



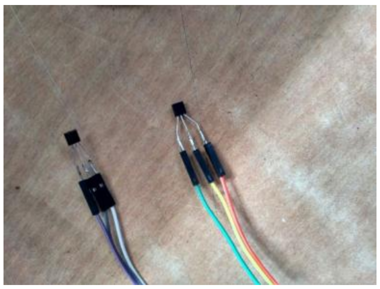
Arduino:
Over the years Arduino has been the brain of thousands of projects, from everyday objects to complex scientific instruments. A worldwide community of makers - students, hobbyists, artists, programmers, and professionals - has gathered around this open-source platform, their contributions have added up to an incredible amount of accessible knowledge that can be of great help to novices and experts a like.

Heart Pulse Sensor
Heart rate data can be really useful whether you're designing an exercise routine, studying your activity or anxiety levels or just want your shirt to blink with your heart beat. The problem is that heart rate can be difficult to measure. Luckily, the Pulse Sensor Amped can solve that problem.

The Pulse Sensor Amped is a plug-and-play heart-rate sensor for Arduino. It essentially combines a simple optical heart rate sensor with amplification and noise cancellation circuitry making it fast and easy to get reliable pulse readings.
Also, it sips power with just 4mA current draw at 5V so it's great for mobile applications.



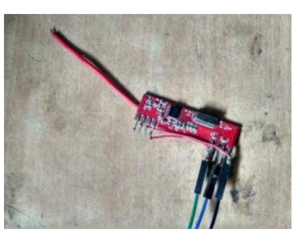
Temperature sensor
The LM35 series are precision integrated-circuit temperature devices with an output voltage linearly-proportional to the Centigrade temperature. This device has an advantage over linear temperature sensors calibrated in Kelvin, as the user is not required to subtract a large constant voltage from the output to obtain convenient Centigrade scaling. This device does not require any external calibration or trimming to provide typical accuracies of ±¼°C at room temperature and ±¾°C over a full −55°C to 150°C temperature range. This device is used with single power supplies, or with plus and minus supplies. As the LM35 device draws only 60 µA from the supply, it has very low self-heating of less than 0.1°C in still air.

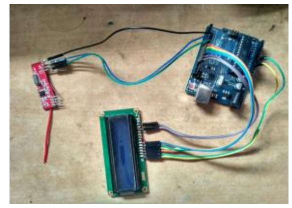


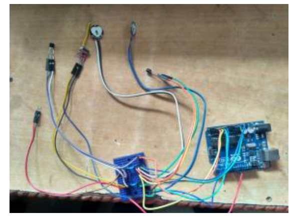
Wireless Transmitter and Reciever
The RF module, as the name suggests, operates at Radio Frequency. The corresponding frequency range varies between 30 kHz & 300 GHz. In this RF system, the digital data is represented as variations in the amplitude of carrier wave.

Transmission through RF is better than IR (infrared) because of many reasons. Firstly, signals through RF can travel through larger distances making it suitable for long range applications. Also, while IR mostly operates in line-of-sight mode, RF signals can travel even when there is an obstruction between transmitter & receiver. RF communication uses a specific frequency unlike IR signals which are affected by other IR emitting sources.

This **RF module** comprises of an **RF Transmitter** and an **RF Receiver**. The transmitter/receiver (Tx/Rx) pair operates at a frequency of **434 MHz**. An RF transmitter receives serial data and transmits it wirelessly through RF through its antenna connected at pin4. The transmission occurs at the rate of 1Kbps - 10Kbps.The transmitted data is received by an RF receiver operating at the same frequency as that of the transmitter.







IV. RESULTS

Advantages
wearable technology yields important patient **accurate** data for improved services by healthcare. Wearables compute data from day to day activities which can be used by physicians to improve diagnosis or treatment. Wearables also offer a hands-free way to communicate information, ensuring a sterile environment to communicate data. And finally, states the report, wearables offer a first person point of view of the user to the medical professional.

Disadvantages
Design and technical difficulties go hand in hand. there is often an issue with waterproofing designs. Sweat and bad weather, such as heat and precipitation, are two sources of damage to the technology. In addition, a device’s small size can result in small and difficult screens to view information as well as “constrained power reserves”.

Applications
Dual sensored monitoring system is employed in healthcare units to accurately evaluate the condition of the patient and necessary actions can be takes accordingly.

V. CONCLUSION

Due to the resource restriction, environmental effects and malicious attacks, and medical sensors inevitably produce unreliable measurements. Therefore, fault detection is very important for BSNs to avoid false medical diagnosis and false alarms.

In this project, we propose a Dual Sensor scheme for fault detection of BSNs

REFERENCES

[1] O. Salem, A. Guerassimov, A. Mehaoua, A. Marcus, and B. Furht, “Sensor fault and patient anomaly detection and classification in

medical wireless sensor networks," in *Proc. IEEE Int. Conf. Commun.*, 2013, pp. 4373–4378.
[2] O. Salem, Y. Liu, and A. Mehaoua, "Anomaly detection in medical wireless sensor networks," *J. Comput. Sci. Eng.*, vol. 7, no. 4, pp. 272–284, 2013.
[3] J. Branch, B. Szymanski, C. Giannella, and R. Wolff, "In-network outlier detection in wireless sensor networks," in *Proc. IEEE Int. Conf. Distrib. Comput. Syst.*, 2006, pp. 51–57.
[4] M. Zhang, S. Shi, H. Gao, and J. Li, "Unsupervised outlier detection in sensor networks using aggregation tree," in *Proc. Adv. Data Mining Appl.*, 2007, pp. 158–169.
[5] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection: A survey," *ACM Comput. Surveys*, vol. 41, no. 3, pp. 1–72, 2009.
[6] J. Liu and N. Kato, "A Markovian analysis for explicit probabilistic stopping based information propagation in post-disaster ad hoc mobile networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 1, pp. 81–90, Jan. 2016.
[7] Y. Zhang, N. Meratnia, and P. Havinga, "Outlier detection techniques for wireless sensor networks: A survey," *IEEE Commun. Survey Tuts.*, vol. 12, no. 2, pp. 159–170, Second Quarter 2010.
[8] W. Wu, X. Cheng, M. Ding, K. Xing, F. Liu, and P. Deng, "Localized outlying and boundary data detection in sensor networks," *IEEE Trans. Knowl. Data Eng.*, vol. 19, no. 8, pp. 1145–1157, Aug. 2007.
[9] B. Sheng, Q. Li, W. Mao, and W. Jin, "Outlier detection in sensor networks," in *Proc. Mobile Ad Hoc Netw. Comput.*, 2007, pp. 219–228.
[10] T. Palpanas, D. Papadopoulos, V. Kalogeraki, and D. Gunopulos, "Distributed deviation detection in sensor networks," *ACM Special Interest Group Manag. Data*, vol. 32, no. 4, pp. 77–82, 2003.
[11] S. Ramaswamy, R. Rastogi, and K. Shim, "Efficient algorithms for mining outliers from large data sets," *ACM Special Interest Group Manag. Data*, vol. 29, no. 2, pp. 427–438, 2000.
[12] T. Cover and P. Hart, "Nearest neighbor pattern classification," *IEEE Trans. Inf. Theory*, vol. IF-13, no. 1, pp. 21–27, Jan. 1967.
[13] S. Rajasegarar, C. Leckie, M. Palaniswami, and J. C. Bezdek, "Distributed anomaly detection in wireless sensor networks," in *Proc. IEEE Int. Conf. Commun. Syst.*, 2006, pp. 1–5.
[14] B. Krishnamachari and S. Iyengar, "Distributed Bayesian algorithms for fault-tolerant event region detection in wireless sensor networks," *IEEE Trans. Comput.*, vol. 53, no. 3, pp. 241–250, Mar. 2004.
[15] X. Luo, M. Dong, andY. Huang, "On distributed fault-tolerant detection in wireless sensor networks," *IEEE Trans. Comput.*, vol. 55, no. 1, pp. 58–70, Jan. 2006.
[16] A. Annichini, E. Asarin, and A. Bouajjani, "Symbolic techniques for parametric reasoning about counter and clock systems," in *Proc. Comput. Aided Verification*, 2000, pp. 419–434.

