ISSN 1000-9825, CODEN RUXUEW
Journal of Software, Vol.18, No.5, May 2007, pp.1208−1217
DOI: 10.1360/jos181208

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http://www.jos.org.cn
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基于加权中值的分布式传感器网络故障检测*

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Weighted-Median Based Distributed Fault Detection for Wireless Sensor Networks

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Gao JL, Xu YJ, Li XW. Weighted-Median based distributed fault detection for wireless sensor networks. *Journal of Software*, 2007,18(5):1208−1217. http://www.jos.org.cn/1000-9825/18/1208.htm

Abstract: The existence of faulty sensor measurements in wireless sensor networks (WSNs) will cause not only a degradation of the network quality of service but also a huge burden of the limited energy. This paper investigates using the spatial correlation of sensor measurements to detect the faults in WSNs. Specially, (1) a novel approach of weighting the neighbors' measurements is presented, (2) a method to characterize the difference between sensor measurements is introduced, (3) a weighted median fault detection scheme (WMFDS) is proposed and evaluated for both binary decisions and real number measurements. Theoretical analysis and simulation results show that the proposed WMFDS can attractively obtain the high detection accuracy and considerably reduce the false alarm probability even in the existence of large fault sets. It is demonstrated that the proposed WMFDS is of excellent performance in fault detection for WSNs.
Key words: wireless sensor network; fault detection; weighted median; spatial correlation; WMFDS (weighted median fault detection scheme)

摘 要: 无线传感器网络中的错误测量数据会导致网络服务质量下降和能量浪费.提出了一种通过融合邻居节点的测量数据来实现故障检测的策略.主要做了以下 3 项工作:(1) 提出了一种新颖的对邻居节点测量数据进行加权的方法;(2) 提出了一种衡量测量数据之间差距的方法;(3) 提出了基于加权中值的故障诊断策略 WMFDS(weighted median fault detection scheme),它同时适用于二进制决策和实数测量值.理论分析及仿真结果表明,即使节点发生故障的概率很高,提出的诊断策略也能得到很高的检测精度和较小的误判率,这表明在无线传感器网络故障检测中应用该方法具有很好的性能.
关键词: 无线传感器网络;故障检测;加权中值;空间相关;WMFDS (weighted median fault detection scheme)

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* Supported by the National Natural Science Foundation of China under Grant No.60633060 (国家自然科学基金); the National High-Tech Research and Development Plan of China under Grant No.2006AA01Z223 (国家高技术研究发展计划(863)); the National Grand Fundamental Research 973 Program of China under Grant No.2005CB321604 (国家重点基础研究发展规划(973))

Received 2006-12-31; Accepted 2007-03-05

中图法分类号: TP393 文献标识码: A

1 Introduction

A wireless sensor network (WSN) consists of a large number of small sensor nodes, which are equipped with sensing, data processing, and communication components. Usually sensor nodes are densely deployed to monitor the environment. During the lifetime of network, the measured data or the detected decisions are transmitted to a base station[1−4].

The resource constraint devices are confronted with the challenges of ensuring accuracy of observations while conserving power resources. Sensor data is subject to several sources of faults, such as hardware crash, security attack, or environment disturbance[5−7]. The faulty data is negative for the networks: (1) it decreases the judgment accuracy of the base station; (2) It increases the traffic in the networks; (3) It wastes much limited energy. Therefore, the networks must identify the faulty sensor data and a localized generic scheme for each node is highly preferred in WSNs.

In this paper, we propose the weighted median fault detection scheme (WMFDS) for WSNs. In many data centric applications of sensor networks, the nearby sensors are likely to have similar measurements. To detect faulty measurements, we assume the faulty measurements are uncorrelated, while normal measurements are spatially correlated. In other words, readings from faulty sensors are geographically independent, but readings from sensors in close proximity are spatially correlated[8].

The rest of the paper is organized in the following way. We first review the literature in the fault detection area in Section 2. Then, we define the network model and fault model in Section 3. A fault detection scheme is proposed in Section 4. We analyze the performance of the proposed scheme in theory in Section 5. After that, the simulate results are presented in Section 6. Finally, the paper is concluded in Section 7.

2 Related Work

Recently, fault tolerance in WSNs has drawn much attention from the researchers[9−13]. Krishnamachari, *et al*.[9] introduced a distributed solution for the binary detection of interesting environmental events. They took into account the possibility of sensor measurement faults and developed a distributed Bayesian algorithm for detecting such faults. They proposed three decision schemes for fault recognition, in which the Optimal Threshold Decision Scheme (OTDS) is the best. Subsequently, Luo, *et al*.[10] discussed how to choose neighbor size and how to address both the noise-related measurement error and sensor fault simultaneously in fault-tolerant detection. However, they didn’t explicitly attempt to detect faulty sensors; instead, they proposed algorithms to improve the event detection accuracy in the presence of faulty sensors. One other shortcoming is that their proposed schemes are only for the binary decision situation.

In Ref.[11], the taxonomy for classification of fault in sensor networks and the first on-line model-based testing technique was introduced. This approach can be applied on an arbitrary system of heterogeneous sensors with an arbitrary type of fault model. However the technique is centralized. It is up to the base station to collect sensor node information and conduct the on-line fault detection.

Using management architecture, a failure detection scheme called MANNA was proposed for WSNs[12]. The scheme created a manager, which has the global vision of the network, to perform complex tasks such as retrieving the node state and detect node failure. However, the centralized management and overhead communication may not realistic for many applications.

A distributed fault detection algorithm was proposed in Ref.[13] to locate the faulty sensors in the WSN. It calculates the measurement difference between neighbor sensors at different time to find if the current measurement of a sensor is different from its previous measurement. If the measurement changes over the time significantly, it is more likely the sensor is faulty. However the algorithm can only detect the fault once for a continuous fault. In other words, when the faulty measurement continues, which is common in WSN, the algorithm can't detect the fault except the first time.

Our WMFDS is a purely localized, generic, scalable fault detection scheme for WSNs. It does not need any physical position information. Even when half neighbors are faulty, it can still successfully identify most of the faulty sensors.

3 Network Model and Fault Model

Our scheme can be applied in network models including grid topology and random topology. Fig.1 shows a sample deployment, which includes 10 percent faulty sensors. In this paper, we don't care for the concrete application such as event detection or environment monitor and only require the spatial correlation in neighbor measurements.

Sensors are considered as neighboring sensors if they are within the transmission range of each other. Each node regularly broadcasts its measured data or binary decision to all its neighbors.

Fault may occur at different levels of the WSN, such as physical layer, hardware, system software, and middleware[14]. As sensors are most prone to malfunction, we focus on the sensor fault by assuming all software is already fault tolerant. That is to say, nodes are still able to receive, send, and process when they are faulty.

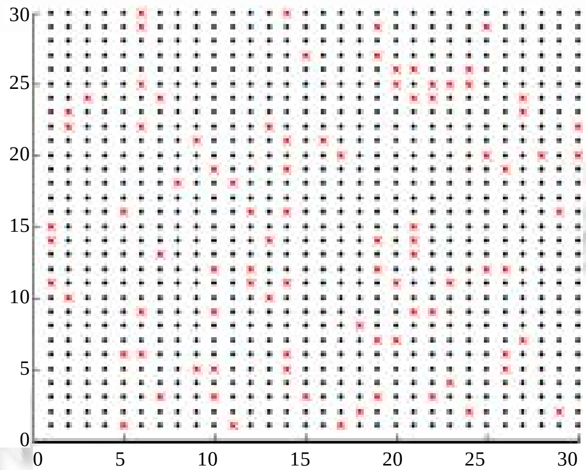

Fig.1 Sensor nodes deployed with uncorrelated sensor faults (denoted as "×")

4 Localized Fault Detection

In this section, we will first give some definitions for the denotations. Then, the weighted median and a measure to the difference between two sensor measurements will be introduced. Lastly we will present the WMFDS.

4.1 Definitions

Table 1 summarizes the notations we will use in our discussion.

Let the measured data of a sensor be x. Some of them may not be accordant to the ground truth. Now we consider the sensor n_i. It has N neighbors and their measured values are x_j (j=1,…,N), and their corresponding weights are λ_j (j=1,…,N), which represent their corresponding confidence degrees. Our objective is to justify whether n_i's measured data x_i is faulty or not by exploiting the neighbor sensors' measurements.

Table 1 Summary of notations

Symbol	Definition
p	Probability of failure of a sensor
n_i	The ith sensor in network.
N	Number of neighbor sensors
x_i	Measurement of sensor n_i
$\hat{x}_i$	Weighted median of n_i's neighbors' measurements
λ	Sensor's confidence degree
$\lambda_{\max}$	Initial confident degree
ξ	The maximum tolerant error range

4.2 Median and weighted median

Firstly, we consider the median of the neighbor sensors' measurements. Assuming x_j (j=1,…,N) are in increasing order, the median can be formulated as follows:

$$\hat{x}_i = \mathrm{MED}\left\{ x_j \,\middle|\, \begin{matrix} N \\ j=1 \end{matrix} \right\} = \begin{cases} x_{\frac{N+1}{2}}, & N \text{ is odd} \\ \dfrac{x_{\frac{N}{2}} + x_{\frac{N}{2}+1}}{2}, & N \text{ is even} \end{cases} \tag{1}$$

where MED is the median operation, which outputs the middle of a distribution: half the values are above the median and half are below the median. Then, we introduce the weighted median based on confidence degree as an extension of median:

$$\hat{x}_i = \mathrm{MED}\left\{ \lambda_j \lozenge x_j \,\middle|\, \begin{matrix} N \\ j=1 \end{matrix} \right\} \tag{2}$$

where $\lozenge$ characterizes duplication operation given by:

$$\lambda_j \lozenge x_j = \overbrace{x_j, x_j, \ldots, x_j}^{\lambda_j \ times} \tag{3}$$

The procedure of the weighted median can be stated as follows: sort the neighbors' readings, duplicate each reading x_j to the number of the corresponding weight λ_j and calculate the median value from the new sequence.

According to the measurement x_i of the sensor node n_i and the weighted median $\hat{x}_i$ of its neighbor sensors' measurements, we define a decision function $f(x_i, \hat{x}_i)$ as follows:

$$f(x_i, \hat{x}_i) = \begin{cases} 1, & \text{if } \left| \dfrac{x_i - \hat{x}_i}{\hat{x}_i} \right| > \xi \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where ξ is a predefined threshold. In WSN applications, ξ is set to the tolerant error ratio of the sensor measurements. That is to say, if the deviation of the measure value from the true value is less than ξ, the measurement is regarded as right.

Based on the decision function, we introduce a definition of confidence degree of a sensor. Let a positive integer λ represent the confidence degree of a sensor. $\lambda_{\max}$ is the initial confidence degree for all sensor. i.e. all λ gets the same $\lambda_{\max}$ as an initial confidence degree at the beginning. During the networks lifetime, we set $\lambda_i=\lambda_i-1$ if $f(x_i, \hat{x}_i)=1$. When λ_i reaches zero, the sensor n_i perhaps fails and its state should be reported to a base station. It is up to the base station to decide the further actions such as repair or replacement etc.

4.3 Fault detection scheme

According to the preliminary work, we propose the weighted median fault diagnose scheme (WMFDS) as the following three steps:

1. Obtain the sensor measurements x_j and the confidence degree λ_j of all N_i neighbors of sensor n_i
2. Calculate the weighted median value $\hat{x}_i$ using Eq.(2)
3. Calculate $f(x_i,\hat{x}_i)$ using (4)

 If $f(x_i,\hat{x}_i)=0$

  x_i is right

 Else

  (i) x_i is faulty

  (ii) Set $\lambda_i=\lambda_i-1$

  (iii) If $\lambda_i=0$, report node failure state to a base station

□

5 Analysis of the Proposed Fault Diagnose Scheme

To make theoretical analysis, we will make the assumption that the difference between normal neighbor sensors' measurements is less than ξ. Let x_k ($k\in[1,N]$) be in increasing order. m is the number of the normal sensors. l is the number of faulty sensors whose measurements are lower than the right measure range and h is that of the higher. Let $\mathfrak{R}_m=\{x_k|l+1\le k\le l+m\}$.

We introduce two metrics to measure the performance. Detection accuracy (P_{00}) is the probability that a faulty sensor is diagnosed as faulty. Similarly, False alarm probability (P_{10}) is the probability that a normal sensor is diagnosed as faulty. In the process of the fault detection, we need to improve the detection accuracy while reducing the false alarm probability. The probability of a sensor being faulty is p ($0\le p\le 1$). We will analyze the detection accuracy and fault alarm rate with respect to various probability p in the following.

5.1 Detection accuracy

When the weighted median belongs to the abnormal measure range (i.e., $\hat{x}_i\notin\mathfrak{R}_m$), a faulty sensor can be diagnosed as good in our WMFDS. Let α_m represent the probability of the weighted median belonging to faulty measurement range

$$\alpha_m=P\left\{\sum_{k=l+1}^{l+m}\lambda_k<\left|\sum_{k=l+m+1}^{N}\lambda_k-\sum_{k=1}^{l}\lambda_k\right|\right\} \tag{5}$$

If the weighted median belongs to the abnormal measure range, partial faults can be detected and the probability β ($0\le\beta\le 1$) is

$$\beta=P\left\{\left|\frac{x_j-x_i}{x_i}\right|>\xi\right\},\forall x_i,x_j\notin\mathfrak{R}_m \tag{6}$$

So far, the detection accuracy can be formulated in the following form

$$P_{00}=1-\sum_{m=0}^{\lfloor N/2\rfloor}\alpha_m(1-\beta)\binom{m}{N}p^{N-m}(1-p)^m \tag{7}$$

If all weights are all the same, the weighted median fault detection scheme becomes a median fault detection scheme (MFDS). And we get the following theorem.

Theorem 1. For detection accuracy, the WMFDS is better than the median fault detection scheme.

Proof: In a given situation, β and p are fixed value to all schemes. From Definition 1, we can draw that

$$\lambda_{k1} \ge \lambda_{k2},\ (k1 \in [l+1, l+m], k2 \in [1,l] \cup [l+m+1, l+m+h]) \tag{8}$$

Then

$$p\left\{\sum_{k=l+1}^{l+m} \lambda_k < \left| \sum_{k=l+m+1}^{N} \lambda_k - \sum_{k=1}^{l} \lambda_k \right| \right\} \le P\{m < |h-l|\} \tag{9}$$

Let P_{00}^{M} represent detection accuracy using the median fault detection scheme, and $\alpha_m^M = P\{m < |h-l|\}$. Formulation (9) can be rewritten as $\alpha_m \le \alpha_m^M$.

Then, we have

$$\begin{aligned} P_{00} - P_{00}^{M} &= \left(1 - \sum_{m=0}^{\lfloor N/2 \rfloor} \alpha_m (1-\beta) \binom{m}{N} p^{N-m} (1-p)^m \right) - \left(1 - \sum_{m=0}^{\lfloor N/2 \rfloor} \alpha_m^M (1-\beta) \binom{m}{N} p^{N-m} (1-p)^m \right) \\ &= \sum_{m=0}^{\lfloor N/2 \rfloor} (\alpha_m^M - \alpha_m)(1-\beta) \binom{m}{N} p^{N-m} (1-p)^m \ge 0 \end{aligned} \tag{10}$$

□

when β is fixed, we can see from Eq.(7) that if $\alpha_m = 0, m \in \left[1, \left\lfloor \frac{N}{2} \right\rfloor\right]$, the detection accuracy P_{00} reaches its upper bound. When $\alpha_m = \alpha_m^M$, the detection accuracy P_{00} reaches its lower bound. Figure 2 shows the theoretical probability of detection accuracy with β=0 and $\beta = \frac{1}{2}$. Detection accuracy decreases monotonically as the increase of sensor fault probability. It also can be drawn that the larger β, the higher detection accuracy.

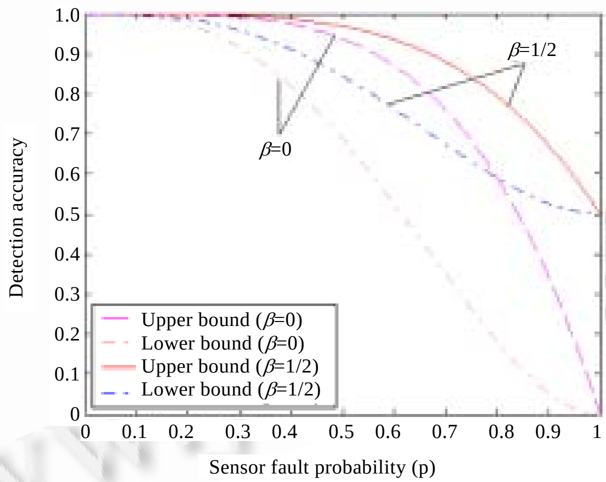

Fig.2 Theoretical detection accuracy (N=4)

5.2 False alarm probability

In WMFDS, a normal sensor is diagnosed as faulty if the weighted median is faulty, the false alarm probability P_{10} is given by

$$P_{10} = \sum_{m=0}^{\lfloor N/2 \rfloor} \alpha_m \binom{m}{N} p^{N-m} (1-p)^m \tag{11}$$

From Eq.(11), it can be drawn that when $\alpha_i = 0, \forall i \in \left[1, \left\lfloor \frac{N}{2} \right\rfloor\right]$, P_{10} reaches its lower bound, and when

$\alpha_i = 1, \forall i \in \left[0, \left\lfloor \frac{N}{2} \right\rfloor\right]$, P_{10} reaches its upper bound.

Figure 3 shows the theoretical value of the false alarm probability. The probability of false alarms is very low, even when the sensor faulty probability is relatively high.

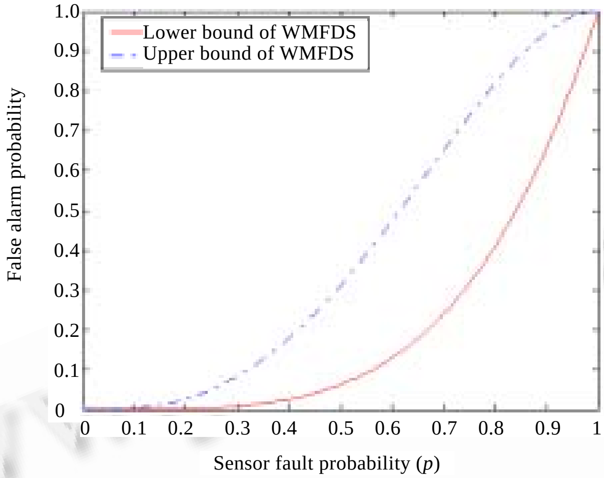

Fig.3 Theoretical probability of false alarm (N=4)

5.3 Analysis of energy consumption

Since WSNs belong to a special category of networks where energy efficiency is critical for their existence[15], we give the analysis of the additional energy consumption in this subsection. Energy consumption of a sensor node can be divided into three domains: sensing, data processing, and communication. Of them, a sensor node expends maximum energy in data communication, which includes transmission, reception, idle, and sleep[1]. The relation can be formulated as follows in general:

$$E_{TRANSMISSION} \approx E_{RECEPTION} \approx E_{IDLE} >> E_{SLEEP} \approx E_{SENSING} \approx E_{DATAPROCESS} \tag{12}$$

When a node transmits its data packets, all its neighbor nodes can receive the packets due to the broadcast feature of radio. A node judges whether its measurement is faulty or not by use of these received packets, instead of requiring any additional packet. So the additional communication energy consumption is little, even equals zero. The energy consumption of data processing correlates with the time complexity of the data fusion algorithms. The detailed comparison of additional energy consumption is shown in Table 2.

Table 2 Comparison of additional energy consumption

Schemes	Additional communication				Sensing	Data processing (time complexity)
	$E_{TRANSMISSION}$	$E_{RECEPTION}$	E_{IDLE}	E_{SLEEP}	$E_{SENSING}$	
OTDS	No	No	No	No	No	$O(n)$
MFDS	No	No	No	No	No	$O(n\log n)$
WMFDS	Transmit/Receive a more byte for each data packet		No	No	No	$O(n\log n)$

From Table 2, we can see that the additional energy consumption for executing fault detection scheme is considerably little compared to the whole energy consumption in the network. Furthermore, by avoiding the detected faulty measured data spreading in the network, a great deal of energy can be saved and the network lifetime can be prolonged.

6 Simulation Results

We conduct some experiments to evaluate the performance of the proposed WMFDS using MATLAB. The scenario consists of 900 nodes placed in a 30×30 square of unit area with grid topology. The communication radius determines which neighbors each node can communicate with and it is set to 1.1 so that each node can only communicate with its immediate neighbor in each cardinal. Binary measurements and real number measurements are simulated respectively in our experiments. We set the threshold λ_{max}=10, ξ=0.1 in our experiments.

6.1 Binary decisions

In many event detection scenarios, only binary decision should be transmitted to a base station. The binary model is obtained by placing a threshold on the measurements of sensors. Each node can get its neighbors' decisions (0 or 1)[8]. Assuming the nodes are placed in event region, a node's binary value is 1 if the sensor node is normal and 0 if the sensor node is faulty. The confidence degree λ is set to 10 for normal sensors and random positive integer less than 10 for faulty sensors. The results of the proposed WMFDS are compared with that of Krishnamachari's Optimal Threshold Decision Scheme (OTDS)[9] with respect to the sensor fault probability *p*. Fig.4 and Fig.5 show the performance measures for the detection accuracy and the false alarm, respectively, with the simulation results of WMFDS and OTDS. Obviously, compared with the OTDS, the detection accuracy is considerably improved and the false alarm rate is highly reduced by using our WMFDS. Especially, when there are about 25% of the sensors being fault, the detection accuracy is about 98% and the false alarm rate is about 1%.

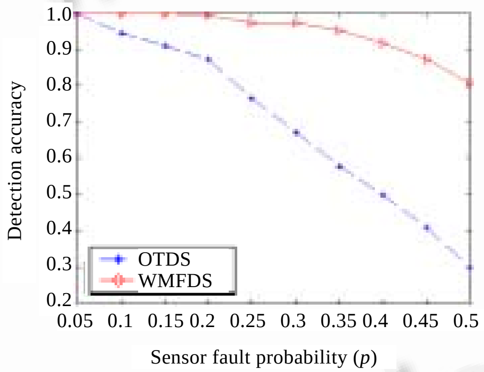

Fig.4 Detection accuracy of binary decisions

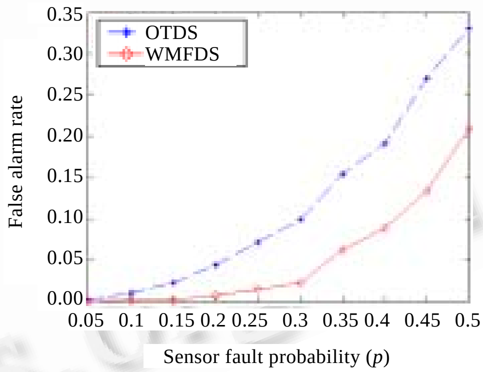

Fig.5 False alarm rate of binary decisions

6.2 Real number measurements

Unlike the OTDS, the WMFDS is capable of dealing with real number measurements in addition to binary decision. In fact, raw data is needed instead of binary decision in many applications, for example in the Great Duck Land experience, they need real temperature, humidity and other data.

The ground truth measurement at a given node in a given instant is denoted with γ. The measured value is denoted as *x*. Generally, the observed measurement x_i of sensor n_i can be represented as:

$$x_i=\gamma_i+\varepsilon_i \tag{13}$$

The noise is modeled as a Gaussian distribution $\varepsilon \sim N(\mu,\sigma^2)$. In the experiences, we simulate four cases according to the typical parameters (Table 3):

In Table 3, $N(\pm 50,1)$ means that ε_i is randomly set to $N(50,1)$ or $N(-50,1)$.

Table 3 Simulation parameters

	γ	ε	λ
Case 1	100	$N(50,1)$	1 for all sensors (i.e. without weight)
Case 2	100	$N(50,1)$	10 for normal sensors; Random integer less than 10 for faulty sensors
Case 3	100	$N(\pm 50,1)$	1 for all sensors (i.e. without weight)
Case 4	100	$N(\pm 50,1)$	10 for normal sensors; Random integer less than 10 for faulty sensors

We repeat the experiment 100 times. The average of detection accuracy and false alarm rate are shown in Fig.6 and Fig.7 respectively. In all case except Case 1, the detection accuracy is fairly high and false alarm rate is considerably low.

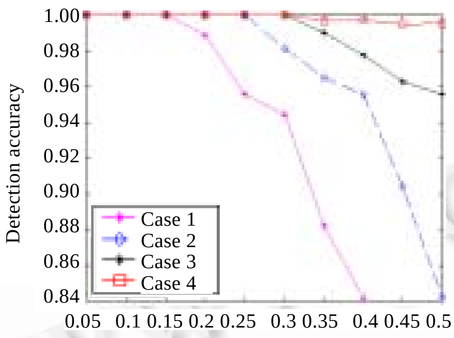

Fig.6 Detection accuracy of real number measurements

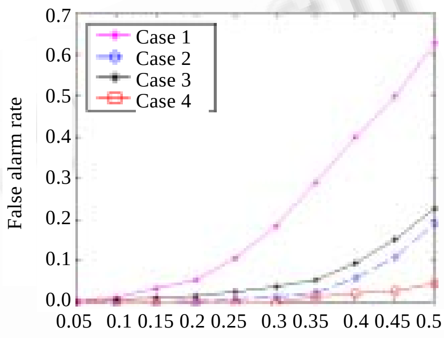

Fig.7 False alarm rate of real number measurements

In Case 1 and Case 3, for all sensors have the same weight, the weighted median degenerates into median. From Fig.6, it can be seen that Case 2 is better than Case 1, and Case 4 is better than Case 3. This is consistent with Theorem 1 presented in Section 5. In our theoretical analysis, Eq.(7) implies that detection accuracy increases with the increasing value of β. Here β equals 0.5 in Case 3 and Case 4, whereas equals 0 in Case 1 and Case 2. In Fig.6, detection accuracy in Case 3 and Case 4 is higher than that in Case 1 and Case 2.

Figure 7 shows the excellent performance of our WMFDS with respect to false alarm rate. By comparing Case 2 and Case 4 with Case 1 and Case 3 in Fig.7, it can be seen that the weighted median has reduced the false alarm rate greatly. Again, this is consistent with our probability analysis.

Overall, our scheme outperforms the pervious fault detection scheme proposed in Ref.[9] in terms of binary decisions. Also our scheme can be applied to real number measurements, and get considerable attractive detection accuracy, at the same time keeping the false alarm rate relatively low.

7 Conclusion

In this paper, we have modeled and analyzed the fault detection scheme based on the spatial correlations among the sensor observations in wireless sensor networks. Both mathematical analysis and simulations show that due to special correlations, most of the fault measurements can be detected. Benefiting from this, significant energy can be saved to prolong the network lifetime by avoiding these faulty measurements transmission in network. The proposed scheme will benefit the research on wireless sensor network by providing a novel way of fault detection.

References:

[1] Akyildiz IF, Su W, Sankarasubramaniam Y, Cayirci E. Wireless sensor networks: A survey. Computer Networks, 2002,38(4): 393–422.

[2] Li JZ, Li JB, Shi SF. Concepts, issues and advance of sensor networks and data management of sensor networks. Journal of Software, 2003,14(10):1717−1727 (in Chinese with English abstract). http://www.jos.org.cn/1000-9825/14/1717.htm

[3] Sun LM, Li JZ, Chen Y, Zhu HS. Wireless Sensor Network. Beijing: Tsinghua University Press, 2005 (in Chinese).

[4] http://www.wsn.org.cn/

[5] Ren FY, Huang HN, Lin C. Wireless sensor networks. Journal of Software, 2003,14(7):1282−1291 (in Chinese with English abstract). http://www.jos.org.cn/1000-9825/14/1282.htm

[6] Elnahrawy E, Nath B. Cleaning and querying noisy sensors. In: Proc. of the 2nd ACM Int'l Conf. on Wireless Sensor Networks and Applications. 2003. 78−87.

[7] Koushanfar F, Potkonjak M, Sangiovanni-Vincentelli A. Error models for light sensors by statistical analysis of raw sensor measurements. In: Proc. of the IEEE Sensors, Vol.3. 2004. 1472−1475.

[8] Vuran MC, Akan OB, Akyildiz IF. Spatio-Temporal correlation: Theory and application for wireless sensor networks. Computer Networks Journal (Elsevier Science), 2004,45:245−259.

[9] Krishnamachari B, Iyengar SS. Distributed Bayesian algorithms for fault-tolerant event region detection in wireless sensor networks. IEEE Trans. on Computers, 2004,53(3):241−250.

[10] Luo X, Dong M, Huang Y. On distributed fault-tolerant detection in wireless sensor networks. IEEE Trans. on Computers, 2006, 55(1):58−70.

[11] Koushanfar F, Potkonjak M, Sangiovanni-Vincentelli A. On-Line fault detection of sensor measurements. In: Proc. of the IEEE Sensors. 2003,2:974−979.

[12] Ruiz LB, Siqueira IG, Oliveira LBe, Wong HC, Nogueira JM, Loureiro AAF. Fault management in event-driven wireless sensor networks. In: Proc. of the 7th ACM Int'l Symp. on Modeling, Analysis and Simulation of Wireless and Mobile Systems. Venice, 2004. 149−156.

[13] Chen J, Kher S, Somani A. Distributed fault detection of wireless sensor networks. In: Proc. of the 2006 Workshop on Dependability Issues in Wireless Ad Hoc Networks and Sensor Networks (DIWANS 2006). 2006. 65−72.

[14] Koushanfar F, Potkonjak M, Sangiovanni-Vincentelli A. Fault-Tolerance in sensor networks. In: Handbook of Sensor Networks. CRC Press, 2004.

[15] George B, Athanassios GK. Energy consumption and trade-offs on wireless sensor networks. In: Proc. of the IEEE 16th Int'l Symp. on Personal, Indoor and Mobile Radio Communications, Vol 2. 2005. 1279−1283.

附中文参考文献:

[2] 李建中,李金宝,石胜飞.传感器网络及其数据管理的概念、问题与进展.软件学报,2003,14(10):1717−1727. http://www.jos.org.cn/1000-9825/14/1717.htm

[3] 孙利民,李建中,陈渝,朱红松.无线传感器网络.北京:清华大学出版社,2005.

[5] 任丰原,黄海宁,林闯.无线传感器网络.软件学报,2003,14(7):1282−1291. http://www.jos.org.cn/1000-9825/14/1282.htm

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