

An Efficient Data Fusion Approach for Event Detection in Heterogeneous Wireless Sensor Networks

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Received: 27 Apr. 2014, Revised: 28 Jul. 2014, Accepted: 29 Jul. 2014

Published online: 1 Jan. 2015

Abstract: This paper concentrates an efficient event detection approach exploiting data fusion technology for the heterogeneous wireless sensor networks. In this type of wireless sensor networks, each sensor is equipped with multiple sensing units. Particularly, in this paper, we study on the data fusion approach based on the type of complementary heterogeneous wireless sensor networks, and the fire disaster detection is utilized as an example of event detection. The proposed event detection model is constructed of data fusion level and information fusion level. In the data fusion level, resource data are collected from the sensors which are both in the sensing field out of the sensing field. In the information fusion level, the event can be detected by computing the data fusion probabilities. For the fire disaster detection process, data collected from temperature sensors and humidity sensors are combined, and then all the measurements are supposed independent on normal random variables. Afterwards, the data fusion process is implemented utilizing genetic algorithm, by which the population is evolved through a predetermined number of consults. Therefore, for each generation of answers, a new set of artificial creatures can be calculated. Furthermore, the answers can be solved by fragments of the most suitable individuals. Finally, experiments are conducted on a series of simulations using the OMNeT++ tool. Compared with other methods, the proposed data fusion based event detection algorithm can effectively find the event through detecting the notify state and alert state, and performs better than other two methods both in the fusion quality and fusion efficiency.

Keywords: Data fusion, Heterogeneous wireless sensor networks, Event detection, Temperature sensor, Humidity sensor

1 Introduction

In recent years, with the rapid development of computer technology and wireless communication technology, the wireless sensor nodes become smaller and can communicate with each other effectively within a limited range. As is well known that wireless sensor nodes have the functions of data sensing, data computing, and information communicating. In a work, the sensors are designed using the idea that wireless sensor networks are constructed utilizing a huge number of sensor nodes. Particularly, sensor networks are designed and developed based on the typical sensors. A sensor network consists of many sensor nodes, which can send message to other sensors through wireless communications [1].

Based on the development of sensor networks, wireless sensor networks have attracted researchers' attentions all over the world in recent years. However, the size of wireless sensors are not big, and the processing ability and computing resources are limited as well. Furthermore, the wireless sensors are more cheap than

normal sensors. The wireless sensor nodes can sense and send information from the environment, and then they can transmit the information packet to users [2].

As is shown in Fig.1, the structure of a typical sensor node is illustrated. A sensor node is made up of 4 sections, including: 1) unit of sensing, 2) unit of processing, 3) unit of transceiver and 4) unit of power. The sensor module and ADC module are usually installed in the wireless sensors, particularly, for the heterogeneous wireless sensor networks, multiple sensing units are installed in the sensor nodes and the analog signals are issued by the wireless sensors and the analog signals are converted to digital signals using the ADC module. As there are process module and memory module in the wireless sensors, the information can be transmitted within the heterogeneous wireless sensor networks effectively. On the other hand, the transceiver module is allocated to send information for the wireless sensor networks. Moreover, the energy supplying component is named power supplied unit, which can

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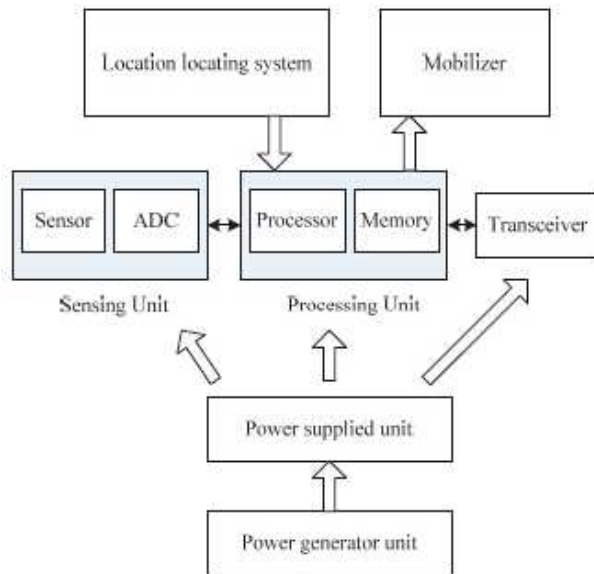


Fig. 1: Illustration of sensor node structure

provide the energy for the whole heterogeneous wireless sensor networks.

There are little infrastructure in the heterogeneous wireless sensor networks, and this networks is made of a large number of sensor nodes which can monitor a specific region to receive data from the environment. Particularly, the wireless sensor networks can be divided into two classes, which are 1) structured wireless sensor networks and 2) unstructured wireless sensor networks. Particularly, the unstructured Wireless sensor networks consist a dense collection of wireless sensor nodes. [3,5]. In this paper, the heterogeneous wireless sensor networks are discussed, which is defined as a specific type of wireless sensor networks several sensing units. That is, in this type of wireless sensor networks, each sensor node has many sensing units and a lot of sensing attribute can be sensed [6,7].

As is shown in Fig.2, sensor nodes of the wireless sensor networks can be divided into 4 categories: 1)Base station node, 2) Cluster head node, 3) Normal sensor node, and 4) Key distribution node. To enhance the communication quality, wireless sensors which are belonged to a same cluster should be placed in the sensing range of the related cluster head. The clocks of cluster head are assumed to be synchronized based on the GPS technology through the base station node. Utilizing the messages which represent the information of nodes' state, each cluster head can collect the information between sensor nodes and cluster node. For the base station, it is made up of the information which is transmitted between different clusters. Therefore, sensors nodes can receive a message from the cluster head, and then send the received message to its neighbors.

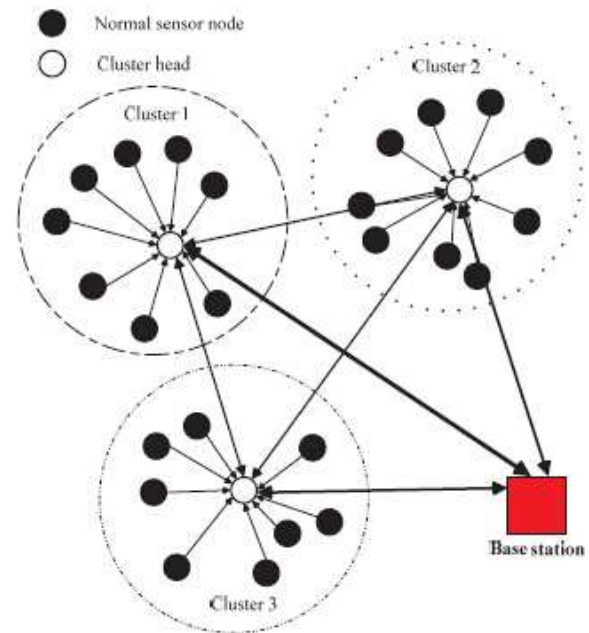


Fig. 2: Structure of the hierarchical wireless sensor networks

Because the power of a wireless sensor node is quite limited, this paper introduce a novel kind of sensor node in the hierarchical wireless sensor networks framework. We aim to reduce normal nodes in the communication constructing phase and the information storing phase. Particularly, in our design, the base station should be located near its related cluster head node to implement a reliable communication.

The computing capability of the base station is quite effective, and its memory capacity is large as well. Furthermore, cluster heads send and receive information with other wireless sensors for a large area. To promote the effectiveness of the wireless sensor networks, each sensor node should communicate to its related cluster node only. On the other hand, information packet can not be transmitted from one normal to another. Furthermore, the cluster head can communicate to each normal sensor in its sensing rage, and can send the information packet to the station. Hence, information can be fused by each cluster head through collaborating with its neighbor sensor node.

Data fusion is defined as the process of integration of multiple data and knowledge. Implement the effective data fusion process based on two data sources (denoted as dimension No.1 and No.2) can lower a classifier superior to each classifier based on the above two dimensions. In this paper, our data fusion process is belonged to the low level data fusion, which can integrate several sources of raw data to generate new raw data. [8,9,10] Furthermore, sensor fusion is also widely utilized in the information

process of wireless sensor networks, which is belonged to the concept of information fusion.

The rest of the paper is organized as the following sections. Section 2 introduces the related works. In section 3, data fusion approach for event detection in heterogeneous wireless sensor networks is illustrated. Section 4 presents the simulation results to make performance evaluation and related analysis is proposed as well. Finally, we conclude the whole paper in section 5.

2 Related works

In this section, we will analyze the related works about the application of data fusion in wireless sensor networks. Data fusion is a powerful tool for wireless sensor networks in many aspects, such as energy saving, target coverage, routing algorithm, data dissemination and so on. Firstly, the data fusion based wireless sensor networks energy saving algorithm is illustrated. As the wireless sensor is powered by battery, the data fusion process in wireless sensor networks should be energy efficient.

Larios et al. presented a novel computational intelligence algorithm designed to optimize energy consumption in an environmental monitoring process: specifically, water level measurements in flooded areas. This algorithm aimed to obtain a trade-off between accuracy and power consumption. The implementation constituted a data aggregation and fusion in itself. A harsh environment can make the direct measurement of flood levels a difficult task [11]. Lin et al. studied on the process and performance of multi-attribute fusion in data collecting of wireless sensor networks. Afterwards, the authors present a self-adaptive threshold algorithm to adjust the different change rates [12]. Luo et al. proposed a new routing algorithm, which is named Adaptive Fusion Steiner Tree (AFST), to effectively collect data with energy constraint. On one hand, AFST can jointly optimize over the costs for both data transmission and data fusion, on the other hand, AFST algorithm can calculate the benefit and cost of data fusion [13]. Different from the above research works, there are other typical works [14,15] about the data fusion based wireless sensor networks energy saving algorithm.

Secondly, coverage problem is an important problem for wireless sensor networks, which can solve the problems of using sensor nodes through building sensor networks to cover regions which should be detected. Considering the difference of regions to be detected, the coverage problem can be divided into two categories, which are "Area Coverage Problem" and "Target Coverage Problem". In this paper, we focus on the "Target Coverage Problem", which aims to detect the state of particularly region in a specific region.

Tan et al. proved that data fusion can effectively enhance sensing coverage by using the collaboration in sensors, and data fusion can lower sensor network density [16]. Furthermore, Xu investigated data fusion method

under the communication constraint between the fusion center and each wireless sensor node [17].

Chen et al. aimed to solve the problem of target location estimation in heterogeneous wireless sensor networks and proposed a novel algorithm using a factor graph to fuse the heterogeneous measured data. In the proposed algorithm, the authors mapped the problem of target location estimation to a factor graph framework and then utilized the sum-product algorithm to fuse the heterogeneous measured data so that heterogeneous sensors can collaborate to improve the accuracy of target location estimation [18].

Thirdly, in wireless sensor networks, the design of information packet routing is of great importance. The reasons lie in that wireless sensor networks have the features which can distinguish other kind of wireless networks, such as mobile ad hoc networks. Moreover, data fusion based routing algorithm has been widely utilized in many application fields, and the related works is illustrated in the following sections.

Lu et al. proposed a distributed data fusion routing (D2F) algorithm, which is designed for deploying distributed data fusion application in wireless sensor networks. D2F can find the optimal route path and fusion placements for a given data fusion tree, which obtains the optimal energy consumption for in-network data fusion. D2F can also handle different link failures and maintain the optimality of energy cost of data fusion by adapting to the dynamic change of network [19]. Luo et al. proposed a routing algorithm which is named called Minimum Fusion Steiner Tree (MFST) to collect data under the power saving policy for wireless sensor networks [20].

Finally, Information fusion for data dissemination in wireless sensor networks is presented in the following subsection.

Nakamura et al. proposed a novel information fusion method (Topology Rebuilding Algorithm (TRA)). In this paper, the network traffic is solved as a signal which can be filtered and translated into evidences [21]. Furthermore, Nakamura et al. also studied on how to use a Dempster-Shafer engine to detect the need for a topology reconstruction [22].

3 Data fusion approach for event detection in heterogeneous wireless sensor networks

3.1 Overview of heterogeneous wireless sensor networks

The wireless sensor networks utilized in the proposed work are organized in heterogeneous mode and equipped with several sensing units. We can see that each sensor in the HWSN is constructed by installing more than one sensing unit. On the other hand, the attributes of each sensing unit are different from each other. To make the explanation more clear, we give an example (shown in Fig.3) to illustrate the structure of HWSN. In Fig.3, the

sensing area for a specific sensor is described as a circle centered at the sensor in its sensing range. In Fig.4, we give a bipartite graph to illustrate an example of target coverage problem with multiple sensing units and multiple attributes.

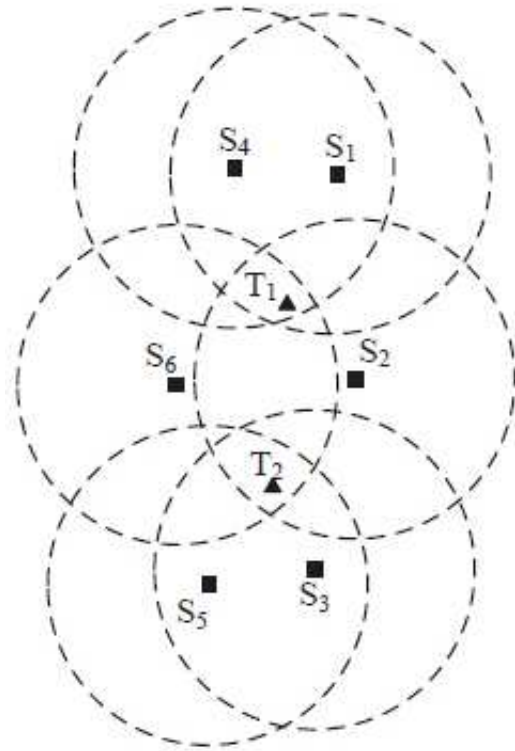


Fig. 3: An example of heterogeneous wireless sensor networks

3.2 The proposed data fusion approach for HWSN

In data fusion field, wireless sensors can be utilized in a wide variety of forms. According to the paper [23], it is possible to classify three different types of wireless sensor fusion, which are "complementary", "cooperative" and "competitive". Particularly, Competitive sensor fusion refers to that if each sensor can deliver independent and redundant measurements of the same phenomenon, providing fault tolerance and robustness to the system. In this paper, we focus on the data fusion approach based on the complementary heterogeneous wireless sensor networks.

In the following section, the formal description of data fusion in heterogeneous wireless sensor networks is given. Supposing $\{X_i\}$ refers to a sequence of several random variables, and then X_i is supposed to have the density of $f(x_i, \mu_0, \sigma)$, where $i \in [1, \tau - 1]$ and the parameter μ_0 is known. Particularly, τ represents the time index which can signal the event. In this paper, we utilize the event of fire disaster happening in forest to test the performance of the proposed algorithm. The data fusion

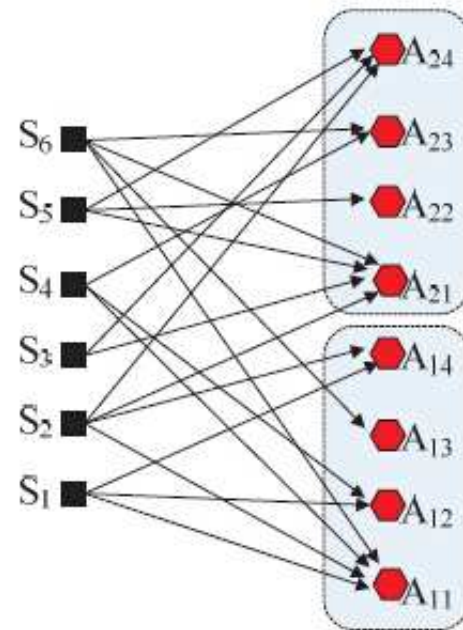


Fig. 4: Illustration of sensing units on sensors and attributes at targets using a bipartite graph

process in fire disaster detection model is shown in Fig.5. As is shown in Fig.5, the proposed the fire disaster detection model is made of data fusion level and information fusion level. In the first level resource data are collected from the sensors in the sensing field and the sensors out of the sensing field. In the second level, the fire disaster is detected by calculating the data fusion probabilities which is obtained by obtaining the generated probabilities. In the proposed fire disaster detection process, two kinds of sensors (temperature sensors and humidity sensors) are integrated together, and we suppose that all the measurements $X_i (i \geq 1)$ do not depend on normal random variables.

For the temperature sensors, the following conditions are satisfied.

$$f(x_i, \mu_0, \sigma) = \frac{e^{-\frac{(x_i - \mu_0)^2}{2\sigma^2}}}{(2\pi\sigma)^{-1/2}} \quad (1)$$

Particularly, for the fire disaster detection, the following hypothesis should be satisfied.

$$f(x_i, \mu_F, \sigma) = \frac{e^{-\frac{(x_i - \mu_F)^2}{2\sigma^2}}}{(2\pi\sigma)^{-1/2}} \quad (2)$$

where the condition $\mu_F > \mu_0$ is satisfied, and μ_0 refers to the average temperature in the absence of fire disaster. Afterwards, we assume that Y_i represents $X_i - \mu_0$ and μ_d represents $\mu_F - \mu_0$. Hence, the absence of fire disaster $Y_i \sim N(0, \sigma^2)$ is satisfied based on the condition

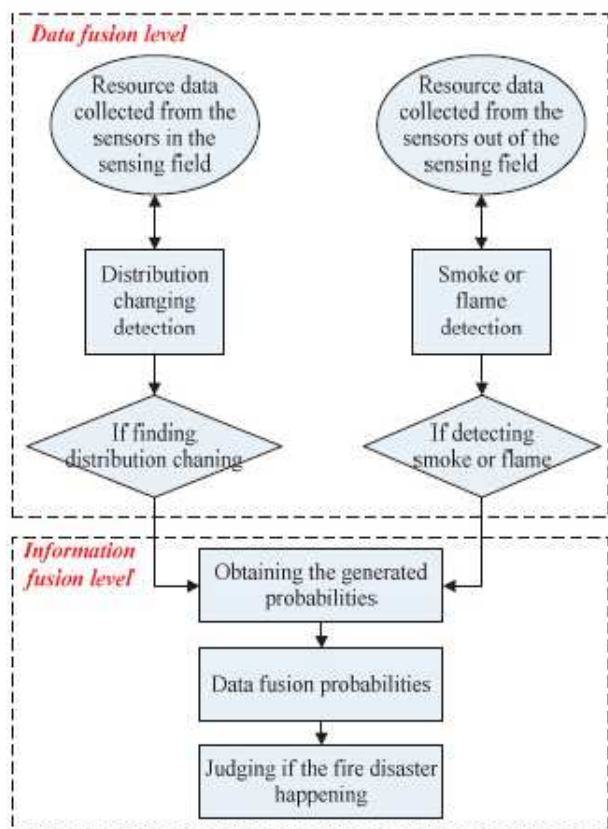


Fig. 5: Structure of the hierarchical wireless sensor networks

$Y_i \sim N(\mu_d, \sigma^2)$. Based on the above hypothesis, the test statistic can be defined as follows.

$$K^{-\frac{1}{2}}W_k = K^{-\frac{1}{2}} \cdot \frac{\sum_{i=1}^k Y_i}{\sqrt{\sum_{i=1}^k \frac{Y_i^2}{k}}} \quad (3)$$

In the process of fire disaster detection, the sensors which can sense humidity should be utilized as well. In the data fusion process, we use μ_0 to represent the ambient relative humidity which is computed in each T_0 minutes through all humidity sensors which are monitored by a LACU unit.

The main innovation of our work lies in that we introduce the genetic machine learning algorithm into the data fusion problem in heterogeneous wireless sensor networks. The genetic algorithm component in the proposed data fusion approach supposes that a population of classifiers for its optimization problem, where individuals are represented by their genotypes. This population is evolved by the genetic algorithm after a predetermined number of consults. At each generation of

answers, a new set of artificial creatures would be obtained. These answers are based on fragments of the most adapted individuals. The proposed data fusion approach based on genetic algorithm is given as follows.

Algorithm 1: Data fusion for heterogeneous wireless sensor networks based on genetic algorithm

Input: E_i, L_{ef}, L_c, C_{sp}

Output: New_{sp}

- (1) E_f is computed by the efficiency solving process;
- (2) if the new E_f is larger than the maximum former E_f then
- (3) $Best_{sp} = Last_{sp}$;
- (4) End If
- (5) $\Delta E_f = 100 \cdot \left(\frac{Last_{ef}}{E_f} - 1 \right)$;
- (6) while ($Rate(reposition) > 0$)
- (7) Crossover();
- (8) Mutate();
- (9) $Rate(reposition) --$;
- (10) End while
- (11) If the system comes into the expert phase then
- (12) $New_{sp} = Best_{sp}$;
- (13) Else if
- (14) $New_{sp} = Current_{sp}$;
- (15) End if

In our fire disaster detection system, two important state are defined("fire disaster notify state" and "fire disaster alert state". For the fire disaster notify state, it means that it is possible that the fire disaster will happen in the short term. On the other hand, fire disaster alert state means the the fire disaster is occurring currently.

Using the genetic algorithm based data fusion approach, the decision can be made to present the alert state. To come into the alert state, several criteria should be defined as follows.

Criteria 1: If the relative humidity sensors are more reliable than the temperature sensors, we can utilize the detection process with the statistic $k^{-\frac{1}{2}} \cdot W_k^H$. Therefore, the condition is set to be true only the following equation is satisfied.

$$k^{-\frac{1}{2}} \cdot W_k^H < T_A(f) \quad (4)$$

where $T_A(f)$ denotes the threshold to be in the alert state. If criteria 1 is satisfied, the system comes into the alert state.

Criteria 2: If the following two equations is satisfied, the proposed system could be switched into alter state

$$(k^{-\frac{1}{2}} \cdot W_k^H < T_H(f)) \cap (k^{-\frac{1}{2}} \cdot W_k^T < T_A(f)) \quad (5)$$

where $T_H(f)$ denotes the threshold to leave the alert state.

Criteria 3: To make the state switching more flexible, the criterion should be satisfi ed.

$$k^{-\frac{1}{2}} \cdot (W_k^T - W_k^H) > \delta_1 \cdot T_A(f) - \delta_2 \cdot T_H(f) \quad (6)$$

where parameters δ_1 and δ_2 are adjusting weights.

To make the decision for the notify state, the lower thresholds are combine together through the minimum

operator to decide when the wireless sensor node will come into to the notify state. if T_N refers to the time instant the fire disaster detection system comes in to the notify sate. Specially, $k^{-\frac{1}{2}} \cdot W_k^T$ and $k^{-\frac{1}{2}} \cdot W_k^H$ represents the test statistic which is utilized in the temperature sensors and humidity sensors respectively. Afterwards, the following equation can be satisfied.

$$T_N = \arg \min_k \{k^{-\frac{1}{2}} \cdot W_k^T > T_N(f) \text{ or } k^{-\frac{1}{2}} \cdot W_k^H < T_H(f)\} \quad (7)$$

According to the conditions in Eq.7, if the parameters of temperature sensor and humidity sensor satisfied the pre-defined conditions, the fire disaster system will come into the notify sate.

4 Simulations

In this section, we will present some simulation results to make performance evaluation for the proposed algorithm. The proposed algorithm is simulated by the OMNeT++ tool [24], and two other methods(Gur Game [25] and IEEE 802.15.4 standard [26]) are utilized to make performance comparison.

We suppose that the sampling rate is equal to 0.5Hz, which means that one sample for each two seconds. Afterwards, we update the estimation of the average temperature every 30 minutes. Therefore, the time window to make a decision is constrained in $N = 30 \times 60 \times 0.5 = 900$ samples. Furthermore, in this simulation, we set two experimental settings to make performance evaluation. In the first experimental settings, a fire takes place 10 minutes after the estimation of the ambient temperature μ_0 . This fire can change an average temperature increase from $\mu_0 = 30$ to $\mu_F = 30$ Celsius degrees ($\mu_d = 30$) at the measurements of one sensor and the standard deviation is taken $\sigma = 5$. Note that IF is an unknown parameter that affects the slope of the drift statistic change. Fig. 6 shows a sample function of the measurements, whereas Fig. 7 shows the evolution of the test statistic.

From the above two figures, we can see that utilizing the aforementioned false alarm rates of $f = 0.01$ and $f = 0.001$, the proposed approach comes to the alert state after 320 samples, and comes to the emergency state after 450 samples. Moreover, although temperature changing from 20 degree to 40 degree, the test statistic used is insensitive to instantaneous changes

The second experimental settings implements the case that the fire front approaches a temperature sensor. A fire event happens ten minutes after the estimation of the average temperature 10 and leads to a gradual increase of temperature at the rate of 0.01 degree per sample. It shows that the average temperature increases one degree in each 3.3 minutes. The initial temperature and the standard deviation are same to the first experimental

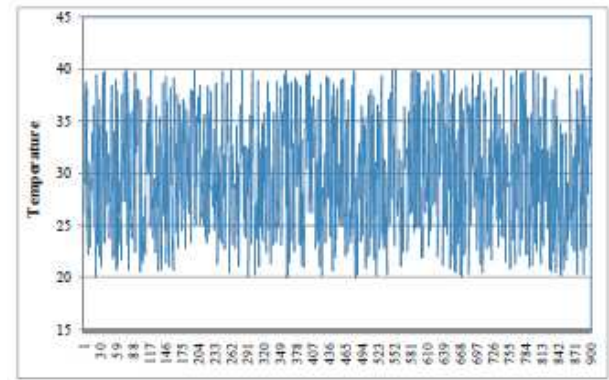


Fig. 6: Structure of the hierarchical wireless sensor networks

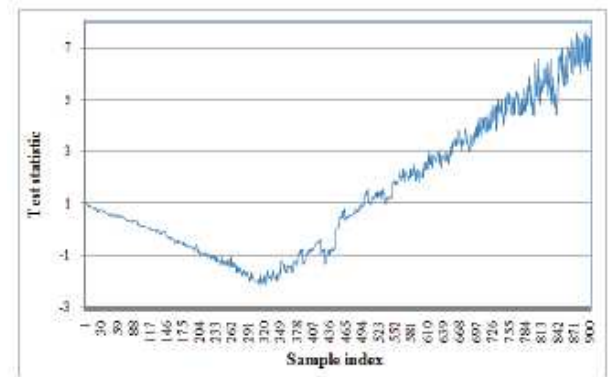


Fig. 7: Structure of the hierarchical wireless sensor networks

settings with $\mu_0 = 30^\circ$ and $\sigma = 5$. Next, the sample function of the measurements and the evolution of the test statistic are given in Fig.8 and Fig.9 respectively.

From the experimental results in Fig.8 and Fig.9, we can see that the proposed approach can realize the change to enter the notify state only after 420 samples. The reason lies in that Since the the rate of temperature change is not high. However, the gradual increase of temperature will lead the system to come into the alert quite fastly after 810 samples.

In the following section , we will test the performance of Information fusion for the proposed algorithm. In scheme 1 used in information fusion process, we suppose that M is equal to one, which means that we integrate the maximum probability induced by the sensors in the sensing field with the fire detection probability of the sensors out of the sensing field. Furthermore, we assume three different fire disaster happening probabilities for the sensor out of sensing field, which are 0.2, 0.4, and 0.9 respectively. Each sensor is fused with three different probabilities, which are 0.1, 0.4,

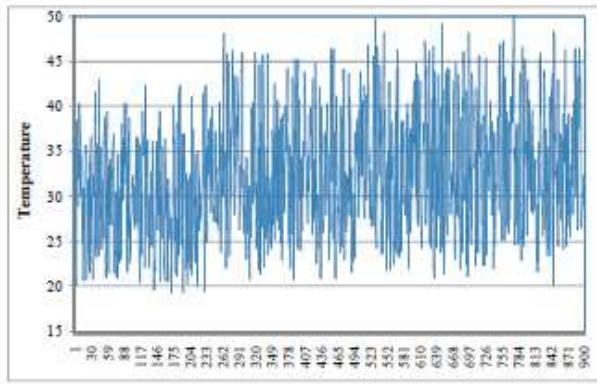


Fig. 8: Structure of the hierarchical wireless sensor networks

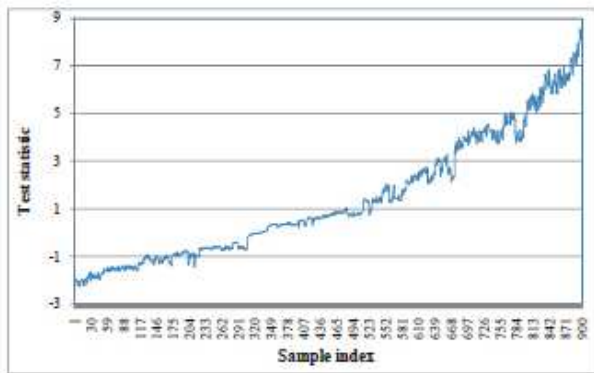


Fig. 9: Structure of the hierarchical wireless sensor networks

and 0.9, inferred by the LACU using sensor measurements within sensing field. Table 1 illustrates the integration results of the proposed data fusion algorithm. From the experimental results in Table.1, we can see that the final probability is kept in fairly small values only if both fused probabilities exceed 0.5. Therefore, the malfunctioning sensor can not be trigger a fire disaster event by itself. Furthermore, when both sensors have high probability values, it will promote the confidence for a fire disaster event detection.

In scheme 2, the value of M is supposed to be equal to 2, which means that we integrate the fused probabilities obtained in scheme 1 with the fire disaster detection probability of another sensor within the sensing field. Next, we suppose that the fire disaster detection probability is equal to 0.3 and 0.7 respectively, and the experimental results are shown in Table.2 and Table.3.

As is shown in Table.2 and Table.3, it can be seen that when all constituent probabilities are greater than a threshold(0.52), a fire disaster event detection can be

Table 1: Data fusion results of scheme 1

Sensor 1	Sensor 2	Conflict	Fusing the two sensors
0.1	0.2	0.22	0.0114
0.1	0.4	0.54	0.1124
0.1	0.9	0.78	0.5217
0.4	0.2	0.51	0.1472
0.4	0.4	0.53	0.5147
0.4	0.9	0.51	0.9214
0.9	0.2	0.71	0.3147
0.9	0.4	0.53	0.7952
0.9	0.9	0.21	0.9832

Table 2: Data fusion results of scheme 2 with the probability of the sensor 2 is equal to 0.3

Sensors fusion	Sensor 2	Conflict	Fusion probability
0.0124	0.3	0.21	0.0024
0.1213	0.3	0.29	0.0267
0.4967	0.3	0.52	0.2114
0.1211	0.3	0.23	0.0178
0.5212	0.3	0.58	0.6007
0.9613	0.3	0.71	0.6816
0.3866	0.3	0.32	0.1024
0.7953	0.3	0.67	0.5188
0.9343	0.3	0.74	0.9307

Table 3: Data fusion results of scheme 2 with the probability of the sensor 2 is equal to 0.7

Sensors fusion	Sensor 2	Conflict	Fusion probability
0.0124	0.7	0.62	0.0126
0.1234	0.7	0.57	0.1232
0.5219	0.7	0.49	0.6639
0.1247	0.7	0.52	0.1414
0.5137	0.7	0.57	0.6872
0.9387	0.7	0.55	0.9687
0.3813	0.7	0.53	0.3007
0.7841	0.7	0.47	0.8203
0.9387	0.7	0.41	0.9547

promoted as it is indicated by the high values of the final fused probability.

Afterwards, two standard metric to evaluation data fusion are utilized: "Quality of fusion(QoF)" and "Efficiency(E)". Efficiency refers to the relation between received and sent messages, and it can be calculated as follows.

$$E = \frac{1}{E_m} \cdot \sum_{i=1}^N R_m \tag{8}$$

where N denotes the number of rounds since the former checkpoint, and R_m, E_m refers to the number of received messages and the number of messages sent by slave sensors respectively. Quality of fusion represents the

average number of the received messages by the master sensor in the process of information monitoring, which can be computed by the following equation.

$$Qof = \frac{1}{N} \cdot \sum_{i=1}^N R_m \quad (9)$$

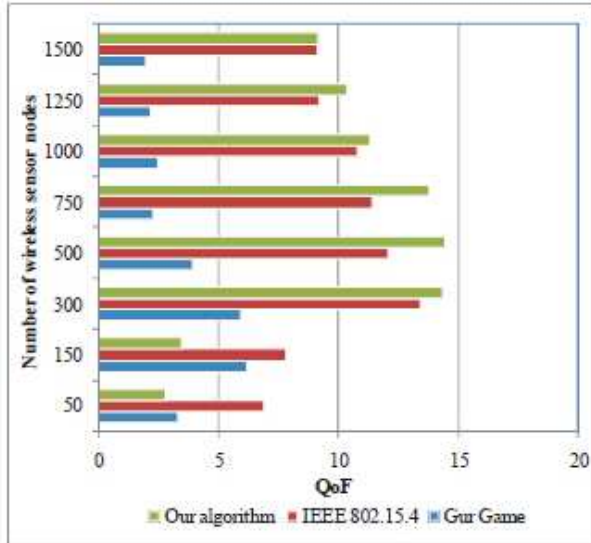


Fig. 10: Performance of QoF comparison under different sensors' density

It can be concluded from Fig.10 and Fig.11 that our algorithm performs better than "IEEE 802.15.4" and "Gur Game" both in the Quality of fusion and Efficiency metric. Each point in the above two figures shows that the average efficiency is obtained after 600 seconds since the simulation process starting. It is possible to notice that our proposed algorithm achieves a higher efficiency than other two methods. The value in efficiency is more than 95% in a network with 300 nodes. Because our algorithm aims to maximize the system efficiency, the efficiency of fire disaster detection is promoted actually, and this case is kept even when the density of wireless sensor networks is high. For example, with 1250 sensor nodes, efficiency of our algorithm is 2.1%, while the related value of IEEE 802.15.4 is 0.9%, and the value is 0.27% for Gur Game. This data shows that our algorithm is more for dense and dynamic heterogeneous wireless sensor networks than other two methods.

Acknowledgment

This research is supported by National Natural Science Foundation under Grant 61371071, Beijing Natural

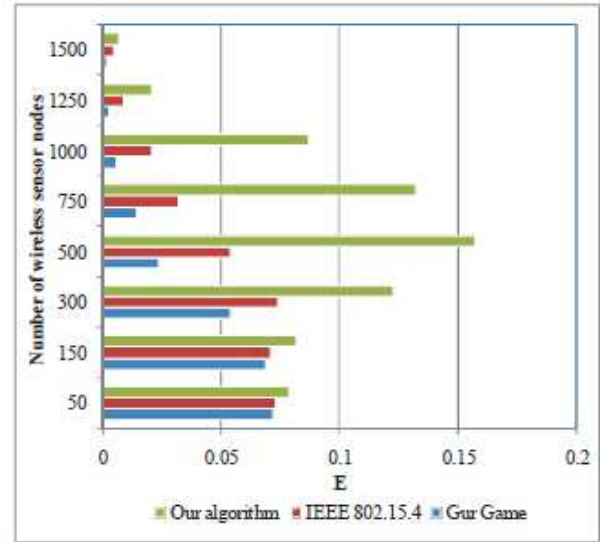


Fig. 11: Performance of Efficiency comparison under different sensors' density

Science Foundation under Grant 4132057 Beijing Science and Technology Program under Grant Z1211

5 Conclusions

In this paper, we present a novel event detection approach exploiting data fusion technology for the heterogeneous wireless sensor networks. In the event detection model, we design data fusion level and information fusion level. In the first level, resource data are collected from the sensors which are both in the sensing field out of the sensing field. In the second level, the events are detected by calculating the probabilities of data fusion. Furthermore, the data fusion results are obtained based on genetic algorithm, by which the population is evolved after a predetermined number of consults. Performance evaluation is implemented utilizing the OMNeT++ tool under different wireless sensor density.

References

- [1] Akyildiz IF, Su W, Sankarasubramanian Y, Wireless sensor networks: a survey, *Computer Networks*, 2002, **38**, 393-422
- [2] Yick Jennifer, Mukherjee Biswanath, Ghosal Dipak, Wireless sensor network survey, *Computer Networks*, 2008, **52**, 2292-2330
- [3] Akyildiz Ian F., Melodia Tommaso, Chowdhury Kaushik R., A survey on wireless multimedia sensor networks, *Computer Networks*, 2007, **51**, 921-960

- [4] Akyildiz Ian F, Melodia Tommaso, Chowdhury Kaushik R, A double key-sharing based false data filtering scheme in wireless sensor networks, *Journal of Computers*, 2013, **8**, 388-398
- [5] Halloush Mohammed, Dawahdeh Tasneem, On varying network coding forwarding ratio in vector based wireless sensor networks, *Journal of Networks*, 2013, **8**, 530-536
- [6] Kuei-Ping Shih, Hung-Chang Chen, Chien-Min Chou, Bo-Jun Liu, On target coverage in wireless heterogeneous sensor networks with multiple sensing units, *Journal of Network and Computer Applications*, 2009, **32**, 866-877
- [7] Guilherme Maiaa, Daniel L. Guidonia, Aline C. Vianab, Andre L.L. Aquinoc, Raquel A.F. Minid, Antonio A.F. Loureiroa, A distributed data storage protocol for heterogeneous wireless sensor networks with mobile sinks, *Ad Hoc Networks*, 2013, **11**, 1588-1602
- [8] Wu QS, Rao NSV, Barhen J, On computing mobile agent routes for data fusion in distributed sensor networks, *IEEE Transactions on Knowledge and Data Engineering*, 2004, **16**, 740-753
- [9] Bass T, Intrusion detection systems and multisensor data fusion, *COMMUNICATIONS OF THE ACM*, 2000, **43**, 99-105
- [10] Lafon Stephane, Keller Yosi, Coifman Ronald R., Data fusion and multicue data matching by diffusion maps, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2006, **28**, 1784-1797
- [11] Larios D. F., Barbancho J., Rodriguez G., Energy efficient wireless sensor network communications based on computational intelligent data fusion for environmental monitoring, *IET Communications*, 2012, **6**, 2189-2197
- [12] Lin Kai, Wang Lei, Li Keqiu, Multi-Attribute Data Fusion for Energy Equilibrium Routing in Wireless Sensor Networks, *KSII Transactions on Internet And Information Systems*, 2010, **4**, 5-24
- [13] Luo Hong, Luo Jun, Liu Yonghe, Adaptive data fusion for energy efficient routing in wireless sensor networks, *IEEE Transactions on Computers*, 2006, **55**, 1286-1299
- [14] Wimalajeewa Thakshila, Jayaweera Sudhannan K., Optimal power scheduling for correlated data fusion in wireless sensor networks via constrained PSO, *IEEE Transactions on Wireless Communications*, 2008, **7**, 3608-3618
- [15] Pai Hung-Ta, Han Yunghsiang S., Power-efficient direct-voting assurance for data fusion in wireless sensor networks, *IEEE Transactions on Computers*, 2008, **57**, 261-273
- [16] Tan Rui, Xing Guoliang, Liu Benyuan, Exploiting Data Fusion to Improve the Coverage of Wireless Sensor Networks, *IEEE-ACM Transactions on Networking*, 2012, **20**, 450-462
- [17] Xu Jian, Li JianXun, Xu Sheng, Data fusion for target tracking in wireless sensor networks using quantized innovations and Kalman filtering, *Science China-Information Sciences*, 2012, **55**, 530-544
- [18] Chen Jung-Chieh, Data Fusion of TOA and AOA Measurements for Target Location Estimation in Heterogeneous Wireless Sensor Networks Using Factor Graphs, *IEICE Transactions On Fundamentals Of Electronics Communications And Computer Sciences*, 2009, **E92A**, 2927-2931
- [19] Lu Zongqing, Tan Su-Lim, Biswas Jit, D2F: A Routing Protocol for Distributed Data Fusion in Wireless Sensor Networks, *Wireless Personal Communications*, 2013, **70**, 391-410
- [20] Luo Hong, Liu Yonghe, Das Sajal K., Routing correlated data with fusion cost in wireless sensor networks, *IEEE Transactions on Mobile Computing*, 2006, **5**, 1620-1632
- [21] Nakamura EF, Nakamura FG, Figueiredo CMS, Using information fusion to assist data dissemination in wireless sensor networks, *Telecommunication Systems*, 2005, **30**, 237-254
- [22] Nakamura EF, Figueiredo CMS, Loureiro AAF, Information fusion for data dissemination in self-organizing wireless sensor networks, *Lecture Notes in Computer Science*, 2005, **3420**, 585-593
- [23] R.R. Brooks, S.S. Iyengar, *Multi-sensor Fusion: Fundamentals and Applications with Software*, Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 1998
- [24] A. Varga, Using the omnet++ discrete event simulation system in education, *IEEE Transactions on Education*, 1999, **42**, 11-25.
- [25] B. Tung, L. Kleinrock, Using finite state automata to produce self-optimization and self-control, *IEEE Transactions on Parallel and Distributed Systems*, 1996, **7**, 439-448.
- [26] IEEE standard for information technology - telecommunications and information exchange between systems-local and metropolitan area networks specific requirements part 15.4: Wireless medium access control (mac) and physical layer (phy) specifications for low-rate wireless personal area networks (wpans), *IEEE Std 802.15.4-2011*, 2011, pp. 1-314.



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