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ORIGINAL RESEARCH

Fire detection by fusing correlated measurements

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Abstract Wireless sensor networks (WSNs) consist of smart nodes that observe a phenomenon of interest (POI) via several sensors. They are extensively used in environment surveillance and can be fit very well in fire detection where detecting fire correctly in real time while avoiding false alarms is crucial. Detection in each node is carried out by fusing the data of the sensors connected to that node. In this paper, a data fusion scheme is proposed in which the measurements of temperature and relative humidity sensors are fused while the correlation among them is resolved using the copula theory. The proposed scheme is validated using a practical data set.

Keywords Copula theory · Correlation · Data fusion · Dependency · Fire detection · Internet of things · Wireless sensor networks

1 Introduction

Fires cause intolerable causalities in both indoor and outdoor environments unless their occurrence can be detected immediately. As an example, forest fires demolish natural resources and even may lead to human death. Thus, immediate detection and suppression of fire is crucial and may be the only way to prevent its damages, especially in outdoor environments such as forests in which wind expands fires rapidly. To this end, the region of interest (ROI) must be monitored continuously. However, traditional methods of fire detection include assigning a person as fire lookout whose job is observing the environment from atop a tower to look for fire. In many cases, fire determination occurs after several minutes or even several hours when the fire has already expansively developed and it is difficult to quench.

Wireless sensor networks (WSNs) are low-cost solutions to fire detection applications. A WSN consists of smart wireless modules— referred to as nodes—capable of data processing , ad-hoc communication and sensing a variety of physical parameters (Karl and Willig 2005). They facilitate remote monitoring and control and hence they are basic to the emerging technology of internet of things (IOT). Deployment of such smart wireless modules enables real-time monitoring of environment and hence avoiding any fire expansion.

Equipped with processing capability, nodes observe the ROI and send their processed data to a fusion center (FC) where the final decision about either fire occurrence (hypothesis F) or not (hypothesis F^c) is taken (Veeravalli and Varshney 2011; Javadi 2016b). In fire detection, it is crucial to detect fire correctly. In other words, fire must be detected just when it occurs and no false alarm must be issued when no fire exists. In fact, reaching very low false alarm rates is vital for increasing the probability of fire occurrence conditioned on an issued fire alarm since fire usually occurs rarely (Papoulis and Pillai 2002; Van Trees 2002).

As an example, assume that fire occurs in a forest with a probability of 2% and a WSN is implemented for fire detection with false alarm rate of 1 percent and the probability of detection equal to 0.99. Then, it is straightforward to show that the probability of fire occurrence conditioned on an alarm is just $P(\text{Fire}|\text{Alarm}) = (0.02 \times 0.99)/(0.02 \times 0.99 + 0.98 \times 0.01)$

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= 0.67. Therefore, the false alarm rate is a very important issue in designing a detector network.

Several examples of implemented fire detection networks are discussed in detail in Zervas et al. (2011), Son et al. (2006), Lloret et al. (2009), Noordin and Ney (2016), May et al. (2014), Bhattacharjee et al. (2012), Cheong et al. (2011), Vijayalakshmi and Muruganand (2016). The authors in Lloret et al. (2009) have proposed to exploit IP-based cameras for verifying fire alarms. When a node detects fire, it sends an alarm to a central server. The central server selects the closest IP camera to the alarming sensor to verify the fire detection. In Zervas et al. (2011) two different false alarms have been exploited for two cases of "notify" and "alert" for possibility of fire and fire occurrence, respectively.

The importance of implementing WSNs for detecting fire in forests has been highlighted in Noordin and Ney (2016) and a GPS-free localization method has been proposed in order to abate the network costs. The effectiveness of WSNs in detecting a fire-in-tunnel incident has been assessed in May et al. (2014) and it has been shown that they potentially improve the situation awareness (SA) due to providing more accurate and reliable information. Another implementation of fire detector network in a coal mine has been presented in Bhattacharjee et al. (2012) in which an algorithm has been proposed in order to bypass the nodes which are damaged due to fire. Moreover, a WSN node structure based on ultraviolet (UV) sensors has been proposed in Cheong et al. (2011) while another structure based on temperature and relative humidity sensors has been presented in Vijayalakshmi and Muruganand (2016).

This paper studies implementation of a fire detector network from the perspective of signal processing. We attempt to improve the performance of a fire detector network by modifying the strategy of decision making rule in each node. Each node decides about fire occurrence by fusing the measurements of the sensors connected to it. It is well-known that considering dependence among node measurements would result in complicated decision rules (Tsitsiklis 1993a; Tenny and Sandell 1981; Blum 1996b). Therefore, it is usually ignored in obtaining the optimal local decision rules (Ciuonzo and Salvo Rossi 2014; Javadi and Peiravi 2012; Ferrari et al. 2011; Viswanathan and Varshney 1997; Chair and Varshney 1986; Niu and Varshney 2005; Niu et al. 2006). However, the more nodes' observations are correlated, the more detection performance degrades (Drakopoulos and Lee 1991).

Correlation among nodes' data has been considered in Ferrari et al. (2014), Luo et al. (2006), Zhu et al. (2008), Willett et al. (2000), Koutsopoulos and Halkidi (2014) in order to improve the network performance. Luo et al. (2006) have proposed to exploit the correlation among nodes in the intermediate nodes during transmitting their data toward the FC in order to aggregate the data during transmission. This problem has been also explored in Zhu et al. (2008) where the correlation among the data of any two nodes has been simply modeled by a correlation coefficient ρ. Willett et al. (2000) have studied the correlation in a two-node network and have shown that there could be conditions in which no optimal decision rule is forthcoming. In addition, they have obtained the sufficient conditions for having an optimal decision rule with a single threshold.

The correlation problem arises in computing the joint probability density function (pdf) of the sensors' observations. To alleviate the problem, estimating the joint pdf using a multivariate Gaussian distribution has been proposed in Koutsopoulos and Halkidi (2014) where it is assumed that the correlation matrix of the sensors' observations is known at the FC and is time-invariant. Apparently, the proposed scheme fails in non-Gaussian noises and in time-variant correlations.

Recently, using the copula theory (Nelsen 2006) has been proposed in order to take the correlation into account (Sundaresan et al. 2011; Iyengar et al. 2011, 2012; Sundaresan et al. 2007; Nelsen 2006). Copulas are functions which couple a multivariate distribution function to its univariate margins (Nelsen 2006) and are useful for handling heterogeneous data. The idea was firstly proposed by Sundaresan et al. (2011) and Sundaresan et al. (2007) where the problem of fusing the decisions of multiple heterogeneous sensors is studied. There, the copula theory has been exploited in calculating the joint probability mass function (pmf) of sensors' decisions at the FC and the performance enhancement has been shown. In fact, their proposed scheme is an extension of the Chair–Varshney (CV) rule (Chair and Varshney 1986) to the dependence case and needs the FC to know the detection performance of the network nodes.

Iyengar et al. (2011) have used copula functions in fusing observations of multiple heterogeneous sensors in order to make a final decision at the FC. It has been proposed to estimate the right copula since modeling the exact joint pdf is very complicated and may be overkilling. The idea has been extended in Iyengar et al. (2012) to the case in which sensors quantize their observations before transmitting to the FC. The authors in He and Varshney (2015) suggest to implement the copula-based distributed detection for fusing censored data. They assume that sensors send their either analog or quantized observations to the FC when they fall outside a single interval identified as "no-send region". Then, the generalized likelihood ratio test (GLRT) has been used at the FC for estimating the most fitted copula function.

In this paper, copula functions are exploited in improving the local decision rules in nodes. We study the scenario in which temperature and relative humidity sensors are connected to each node based on which a local decision is taken. Then, the data of the nodes are transmitted to the FC. Considering the correlation would improve local detection performance which will result in improvement of the system detection performance (Tenny and Sandell 1981) even if the fusion rule at the FC assumes independence among nodes' decisions conditioned on each hypothesis.

The contribution of this paper is improving the performance of a fire detector network by exploiting copula functions in local nodes for fusing the data of their sensors. In fact, while correlation was ignored in previous works, we have shown that considering it in a two-level fusion scheme (one fusion in local nodes and the other one at the FC) would result in a performance gain, especially in very low false alarm rates as shown in Fig. 5. Note that the gain has obtained in nodes with just two sensors. Therefore, we can reach very low false alarm rates with an acceptable detection probability in a very simple node structure, i.e. with just two sensors per node (Fig. 1). Apparently, the performance would improve if simultaneously more sensors were used and correlation among them were considered. It is also worth noticing that previous works have used copula functions just at the FC for fusing heterogeneous sensors while we exploit them locally in nodes.

The rest of the paper is organized as follows. Section 2 discusses the system model used and explains detection by fusing the measurements of sensors. The copula theory and its use in detection are discussed in Sect. 3. The data modeling methods are presented in Sect. 4. The evaluation results of our proposed scheme is presented in Sect. 5. Finally, the paper is concluded in Sect. 6.

Notations: Throughout this paper, we use F for denoting fire occurrence and F^C for the alternate hypothesis. k is the number of sensors connected to each network node while n denotes the number of network nodes. The detection thresholds at the FC and node l are denoted by T and T_l, respectively while the decision of node l is denoted by u_l. In addition, $\mathbb{F}(.)$ and $f(.)$ stand for the cumulative distribution function (cdf) and the probability distribution function (pdf), respectively. Moreover, t and h are used for denoting temperature and relative humidity, respectively. Also, bold letters are used for denoting vectors.

2 System model and data fusion

In this section, the system model and the fusion rules used in this paper are discussed.

2.1 System model

In this paper, we consider a WSN with parallel configuration as shown in Fig. 1. In this configuration, each wireless node consists of two sensors: temperature sensor and relative humidity sensor. Node l takes a local decision u_l by fusing the data of its sensors and transmits it to the FC. The FC is in charge of making a final decision by using an appropriate fusion rule.

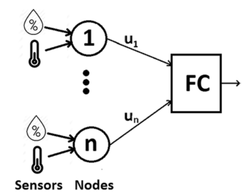

Fig. 1 The network configuration studied in this paper. Each node includes two sensors: temperature and relative humidity. Each node takes a local decision by fusing the data of the sensors and send its decision to the fusion center (FC)

Therefore, data fusion occurs in two levels: the network nodes fuse the data of sensors connected to them and the FC fuses the decisions of all network nodes in order to make a final decision.

2.2 Data fusion

It is well-known that the optimal decision rule would be a likelihood ration test (LRT) which is given by Kay (1998):

$$\Lambda_l(\mathbf{r}_l) = \frac{f(\mathbf{r}_l|F)}{f(\mathbf{r}_l|F^c)} \underset{F^c}{\overset{F}{\gtrless}} T_l \tag{1}$$

where $\Lambda_l(\mathbf{r}_l)$ is the likelihood ratio (LR) of node l, F indicates fire occurrence, F^c is the alternate hypothesis (no fire), T_l is the detection threshold used in node l and $\mathbf{r}_l$ is the vector of the observations of node l.

The statistical information of the sensors' observations is usually not available under F since it depends on the location and the specifications of the fire. The generalized LRT (GLRT) is usually adopted under these circumstances in which the maximum likelihood (ML) estimation of the nuisance parameters are used for computing the probabilities. It is well-known that the GLRT works well in practice (Kay 1998) and it has been proved in Fang and Li (2009) that computationally efficient algorithms can be obtained in some relevant cases. However, other tests such as Rao test (Ciuonzo et al. 2013a, b) and locally optimum detector (LOD) (Blum and Kassam 1992; Blum 1996a) may be adopted when ML estimation calculations become intractable. It is shown in Kay (1998) that the Rao test asymptotically performs the same as the GLRT.

In this paper, the data of sensors is fused using GLRT since there are just two sensors:

$$\Lambda_l(\mathbf{r}_l) = \frac{\sup f(\mathbf{r}_l|F)}{f(\mathbf{r}_l|F^c)} \underset{F^c}{\overset{F}{\gtrless}} T_l\,. \tag{2}$$

Here, it is assumed that the statistics of observations are known under F^c.

The GLRT needs the conditional joint pdf of the observations of the sensors to be known. One may assume conditional independence among sensors' observations which results in:

$$\Lambda_l^{ind}\left(\mathbf{r}_l\right) = \frac{\sup \prod_{i=1}^{k} f\left(r_{li}|F\right)}{\prod_{i=1}^{k} f\left(r_{li}|F^c\right)} \tag{3}$$

where $\Lambda_l^{ind}\left(\mathbf{r}_l\right)$ is the LR of node l assuming independent sensors' observations and k is the number of sensors connected to node l.

The measurements are correlated since all sensors observe the same phenomenon. Considering the correlation would effectively improve the local detection performance (Drakopoulos and Lee 1991) which would result in improvement in the system detection performance at the FC (Tenny and Sandell 1981). On the other hand, any local decision rule must meet the resource limitations of WSN nodes such as limitations in memory, processing capabilities and power (Karl and Willig 2005). In other words, practical implementations need local decision rules to be as simple as it could be.

Each node computes its LR based on (2) and then sends its quantized value to the fusion center (FC) where a final decision is taken by fusing the nodes' data. The number of quantization levels is determined by a bandwidth limitation. In the extreme case, nodes send just one bit indicating their decision about fire occurrence.

A popular fusion rule in the literature is the counting rule (Niu and Varshney 2005) in which all decisions are treated equally:

$$\sum_{l=1}^{n} u_l \underset{F^c}{\overset{F}{\gtrless}} T \tag{4}$$

where u_l is the decision of node l. There are modifications of the counting rule in Javadi and Peiravi (2015) and Katenka et al. (2008). It has been shown in Ciuonzo et al. (2015) that the counting rule yields a robust performance when detection performance of network nodes is not known by the FC.

As mentioned in previous subsection, fusion occurs in two levels in the configuration studied in this paper. Nodes may use the fusion rule (2) since the sensors are connected to them. However, the FC may use either the counting rule (4) or a modification of it since nodes—with bandwidth and energy limitations—transmit data via wireless channels.

Note that the quality of the communication channels affects the overall detection performance. As an instance, if the counting rule is adopted for fusing the decisions of network nodes, $\Lambda_{FC} = \sum_{l=1}^{n} u_l$ would be binomial distributed with the local false alarm rates (p_{f_l}) as its parameter in ideal communication channels. If the channel is modeled as a binary symmetric channel (BSC) with error probability ϵ_l, the counting fusion rule would be distributed as $\Lambda_{FC} \sim bino(n, p_{f_l}(1-\epsilon_l) + (1-p_{f_l})\epsilon_l)$. In this paper, the communication channels between nodes and the FC are considered as ideal since the focus is studying the effect of correlation among sensors' observations.

3 Copula theory

Copulas are functions which relate univariate marginal distributions to a valid multivariate distribution (Nelsen 2006; Schmidt 2007). In other words, a copula is a multivariate cumulative distribution function (cdf) defined in $[0,1]^m$ with standard uniform marginal distributions. The following theorem—known as *Sklar's theorem* – is central in using copulas in statistical signal processing.

Theorem 1 *Let $\mathbb{F}$ be an m-cdf with marginal distributions $\mathbb{F}_1, \mathbb{F}_2, ..., \mathbb{F}_m$. Then, there exists a copula $\mathbb{C}$ such that for all $x_1, ..., x_m$ in $[-\infty, +\infty]$*

$$\mathbb{F}\left(x_1, x_2, ..., x_m\right) = \mathbb{C}\left(\mathbb{F}_1\left(x_1\right), \mathbb{F}_2\left(x_2\right), ..., \mathbb{F}_m\left(x_m\right)\right). \tag{5}$$

If $\mathbb{F}_i$ is continuous for $1 \le i \le m$, then $\mathbb{C}$ would be unique, otherwise it is determined uniquely on $Ran\mathbb{F}_1 \times \cdots \times Ran\mathbb{F}_m$ where $Ran\mathbb{F}_i$ is the range of cdf $\mathbb{F}_i$. See Nelsen (2006) for the proof.

An important result of the Sklar's theorem is obtained by differentiating both sides of (5) which gives the joint pdf as follows:

$$f\left(x_1, x_2, ..., x_m\right) = \left(\prod_{i=1}^{m} f_i\left(x_i\right)\right) c\left(\mathbb{F}_1\left(x_1\right), \mathbb{F}_2\left(x_2\right), ..., \mathbb{F}_m\left(x_m\right)\right) \tag{6}$$

where $f_i(.)$ is the marginal pdf and $c(.)$ is the copula density defined by

$$c\left(v_1, ..., v_m\right) = \frac{\partial^m \mathbb{C}\left(v_1, ..., v_m\right)}{\partial v_1 ... \partial v_m}. \tag{7}$$

Relation (6) is the key in inference problems for computing the joint pdf instead of assuming statistical independence. It describes how marginals are coupled together and hence makes it possible to study marginal pdfs and copula functions separately. Interestingly, many dependence structures can be characterized by just a finite number of well-defined copula functions (Nelsen 2006), some of them are listed in Table 1. These copula functions usually contain a parameter which quantifies dependence.

Accurately modeling of pdfs is not usually necessary (Iyengar et al. 2011; Silverman 1986). In fact, considering an estimate of the dependence structure would considerably improve the system performance. Therefore, an application-specific method proposed by Iyengar et al. (2011) is adopted in this paper for modeling dependence in local decision making.

We assume that the observations of sensors are correlated just when fire occurs. It is well-known that considering correlation makes the optimization problem of decentralized detection intractable (Tsitsiklis 1993a). Our goal is to get distance from independence assumption with as low computation burden as possible. On the other hand, correlation is higher when fire occurs than when no fire exists. Then, it would be wise to assume independence conditioned on no fire occurrence and to consider correlation conditioned on the alternative hypothesis since considering correlation under both hypotheses imposes a high computational burden (Iyengar et al. 2011).

Therefore, the sensors' observations are assumed to be uncorrelated when no fire occurred. Using this assumption, the GLRT (2) turns to:

$$\Lambda_l(\mathbf{r}_l) = \frac{\sup \prod_{i=1}^{k} f(r_{li}|F) c_F(\mathbb{F}_{l1}(r_{l1}|F), \ldots, \mathbb{F}_{lk}(r_{lk}|F); \phi_F|F)}{\prod_{i=1}^{k} f(r_{li}|F^c)} \underset{F^c}{\overset{F}{\gtrless}} T_l \tag{8}$$

where $c_F(.)$ is the best-fit copula with parameter ϕ_F. The above relation can be rewritten as:

$$\Lambda_l(\mathbf{r}_l) = \Lambda_l^{ind}(\mathbf{r}_l) c_F(\mathbb{F}_{l1}(r_{l1}|F), \ldots, \mathbb{F}_{lk}(r_{lk}|F); \phi_F|F) \tag{9}$$

where $r_{lj}(i)$ is the ith sample of sensor j which is connected to node l. In this circumstance, it has been shown in Iyengar et al. (2011) that the best copula function would be approximated by

$$c_F(.) = \arg \max_{c \in C} \sum_{i=1}^{L} \log c\big(\mathbb{F}_1(r_{l1}(i)|F), \ldots, \mathbb{F}_k(r_{lk}(i)|F)\big) \tag{10}$$

in which C is the set of well-defined copula functions and L is the number of samples of observations under fire existence. Therefore, the best-fit copula may be found by simply full-search all well-defined copula functions and be set for local LR computations in nodes. Note that the complexity of the search doesn't impose any computation burden on nodes since it may be accomplished offline before setting up the nodes.

4 Data modeling

A temperature sensor together with a relative humidity sensor are used to detect fire occurrence. When fire occurs, temperature soars while relative humidity drops dramatically. The two parameter variations can filter any other background conditions. For example, when it rains, relative humidity is high which is not an indication of fire occurrence. Or the temperature is low in winter. However, some set values may be adjusted in network nodes according to the date.

In this section, a model of the temperature and the related humidity in different distances from a flame is presented. The model used in simulations is as follows:

$$\theta(d) = \frac{1}{4}\theta_f \left(\frac{h_f l_f}{2\pi d^2}\right)^{1/4} \tag{11}$$

$$RH = \frac{E_s}{0.6108} \exp\left(\frac{-17.27\tau(d)}{\tau(d) + 237.3}\right) \times 100 \tag{12}$$

where $\theta(d)$ is the temperature at distance d from the flame in Kelvin, θ_f is the temperature of the flame in Kelvin, h_f and l_f are the height and the length of the flame, respectively, RH is the relative humidity which is a function of the temperature $\tau(d)$ in Celsius, i.e. $\tau(d) = \theta(d) - 273$ and E_s is a constant computed based on a given temperature and

Table 1 The set of well-defined copula functions

Copula function	Parametric form	Parameter range
Gaussian	$\Phi_\Sigma(\Phi^{-1}(v_1), \ldots, \Phi_{-1}(v_S))$	$\Sigma = [\rho_{mn}], m, n = 1, \ldots S$ $\rho_{mn} \in [-1, 1]$
Student-t	$t_{v,\Sigma}(t_v^{-1}(v_1), \ldots, t_v^{-1}(v_S))$	$v \geq 3$: degrees of freedom
Clayton	$\left(\sum_{n=1}^{S} v_n^{-\phi} - 1\right)^{\frac{1}{\phi}}$	$\phi \in [-1, \infty]\backslash\{0\}$
Frank	$-\frac{1}{\phi}\log\left(1 + \frac{\prod_{n=1}^{S}[e^{-\phi v_n} - 1]}{e^{-\phi} - 1}\right)$	$\phi \in \mathbb{R}\backslash\{0\}$
Gumbel	$\exp\left\{-\left(\sum_{n=1}^{S}(-\ln v_n)^{\phi}\right)^{\frac{1}{\phi}}\right\}$	$\phi \in (1, \infty)$

humidity. This model is adopted from the Stefan-Boltzmann law (Rossia et al. 2010; Rybicki and Lightman 1979; Duffie and Beckman 2013) in equilibrium. In simulations, $\theta_f = 1800$ K, $h_f = 2$ m and $l_f = 1$ m are used in modeling the flame (similar to those used in Rossia et al. (2010)). As an example, Fig. 3 shows the computed temperature and relative humidity in the nodes of the network shown in Fig. 2. Generally, the relative humidity diminishes in the vicinity of the fire where the temperature is high based on models (11) and (12).

Note that the network size is a design parameter which is based on the features of sensors used as well as a desired detection performance. A sparse network of expensive and precise sensors performs the same as a dense network of low-cost sensors (Javadi 2016a). However, it has been shown in Tsitsiklis (1993a), (b), Niu et al. (2006) that distributed detection performs optimally in large network sizes.

The data-set provided by the SensorScope project at the EPFL University (Vetterli 2017) is used in order to extract the statistical model of the sensors. As shown in Fig. 4, the noise of both temperature and humidity sensors can be modeled as Gaussian random variables with the calculated means and variances. This model is used in our simulations. The means under fire occurrence are calculated based on the models (11) and (12). Therefore, the distributions are as follows:

$$\begin{aligned} t|F^c &\sim N\left(\mu_{F^c}, \sigma_t^2\right) \\ t|F &\sim N\left(\mu_F, \sigma_t^2\right) \end{aligned} \tag{13}$$

$$\begin{aligned} h|F^c &\sim N\left(\eta_{F^c}, \sigma_h^2\right) \\ h|F &\sim N\left(\eta_F, \sigma_h^2\right) \end{aligned} \tag{14}$$

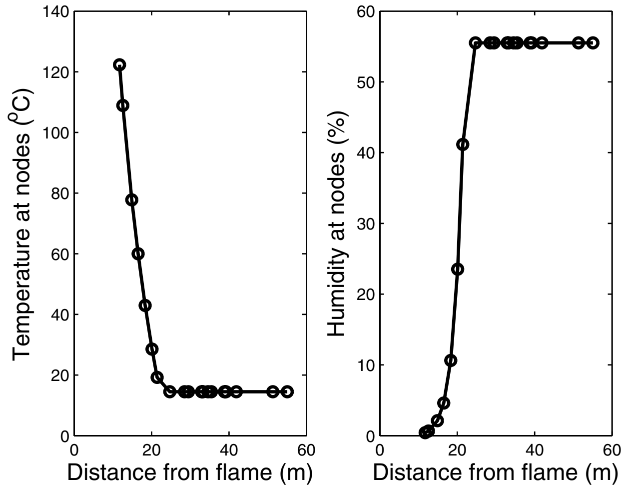

Fig. 3 The computed temperature and relative humidity in the nodes of the network shown in 2. The flame parameters used are $\theta_f = 1800$ K, $h_f = 2$ m and $l_f = 1$ m

where t and h are the measured temperature and humidity, respectively, μ_F (μ_{F^c}) and η_F (η_{F^c}) are the means of temperature and humidity, respectively, when fire (no fire) occurs and σ_t^2 and σ_h^2 are their variances. Based on the data set used, $\mu_{F^c} = 28\,°$C, $\eta_{F^c} = 40$, $\sigma_t = 0.4$ and $\sigma_h = 3.8$ are used in performance evaluation while μ_F and η_F are calculated using (11) and (12). In other words, when fire ignites, the temperature at the location of each node is calculated using (11) based on the fire specifications (i.e. l_f, h_f and θ_f) and its distance from each node. Then, relative humidity at the location of each node is calculated using (12).

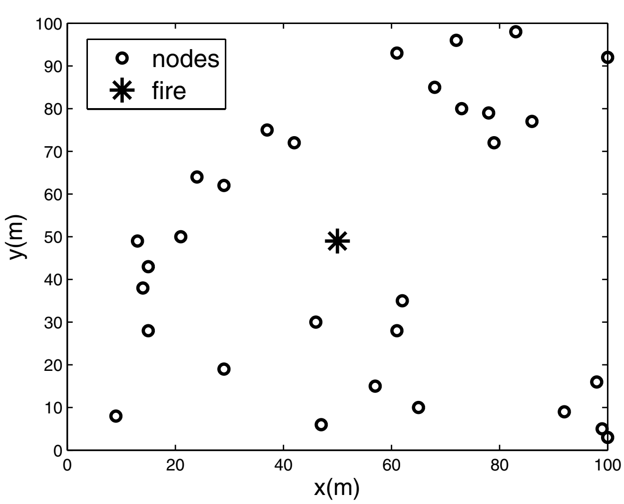

Fig. 2 A network of 30 nodes which is supposed to detect fire occurrence

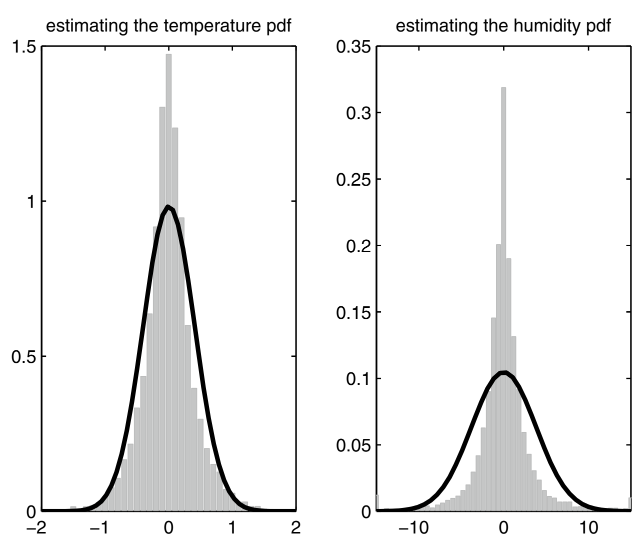

Fig. 4 Estimation of the noise of the temperature and the relative humidity sensors by Gaussian random variables

5 Evaluation results

In this section, we evaluate the copula-based fire detection scheme. 20 wireless nodes are deployed randomly in a 100 m × 100 m region. Each node is equipped with two sensors: temperature sensor and relative humidity sensor. The measurements of the sensors are contaminated by Gaussian noise. Assuming conditional independence between the two sensors' measurements, the GLRT is given by:

$$\Lambda_l^{ind} = \frac{\sup f_t(t;\mu_1|F) f_h(h;\eta_1|F)}{f_t(t|F^c) f_h(h|F^c)} \underset{F^c}{\overset{F}{\gtrless}} T_l^{ind} \tag{15}$$

which results in:

$$\sum_{m=1}^{M} \left\{ \left(\frac{t_{ml} - \mu_{F^c}}{\sigma_t} \right)^2 + \left(\frac{h_{ml} - \eta_{F^c}}{\sigma_h} \right)^2 \right\} \gtrless T_l^{ind} \tag{16}$$

where t_{ml} and h_{ml} denote the mth sample read by the temperature and relative humidity sensors, respectively, M is the number of samples used for local decision making and T_l^{ind} is the node-level threshold assuming conditional independence. In simulations, $M = 10$ has been used.

In order to consider correlation under F, an appropriate copula function should be chosen. Criterion (10) gives the Gaussian copula function as the best-fit with the relevant parameter ϕ_F. Using (8), the explicit form of the local statistics is obtained as:

$$\begin{aligned}\Lambda_l = \frac{1}{2M(1-\phi_F^2)} &\left[\left(\frac{\sum_{m=1}^{M} t_{ml}}{\sigma_t} \right)^2 + \left(\frac{\sum_{m=1}^{M} h_{ml}}{\sigma_h} \right)^2 \right] \\ &- 2\left(\mu_{F^c} \sum_{m=1}^{M} t_{ml} + \eta_{F^c} \sum_{m=1}^{M} h_{ml} \right) - \frac{\phi_F^2}{(1-\phi_F^2)} \left(\sum_{m=1}^{M} t_{ml}^2 + h_{ml}^2 \right) \\ &+ \frac{\phi_F}{(1-\phi_F^2)\sigma_t\sigma_h} \sum_{m=1}^{M} t_{ml} h_{ml} - \frac{1}{M} \sum_{m=1}^{M} t_{ml} \sum_{m=1}^{M} h_{ml}.\end{aligned} \tag{17}$$

Since obtaining the distribution of the above statistic is complicated, the local threshold T_l can be computed by simulation as follows. A large number (say $S = 1000$) of samples of temperature and relative humidity is generated according to their distribution under F^c. The statistic Λ_l is computed for the samples and successively sorted in an ascending order. Then, for the network false alarm probability P_F, the $(1 - P_F)S$ th value is chosen as the threshold.

Running over 5000 Monte Carlo simulations result in Fig. 5. The copula-based detection has been compared against two methods:

- Conditional independence among sensors' observations, i.e. (16).

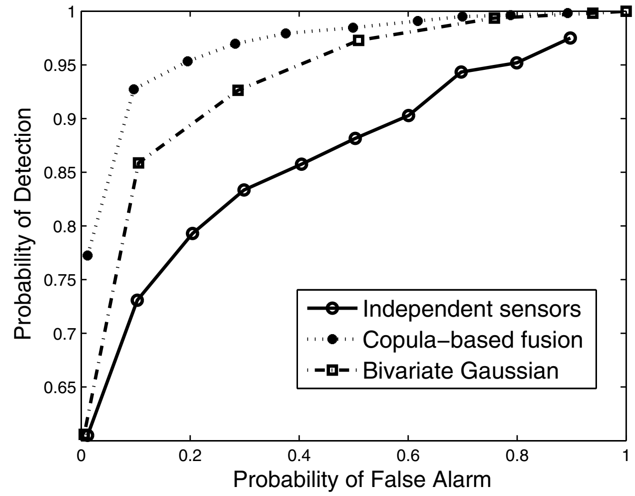

Fig. 5 The local receiver operating characteristics (ROC) based on over 5000 Monte Carlo trials

- A modification of the multivariate-Gaussian-pdf-based method proposed in Koutsopoulos and Halkidi (2014). In Koutsopoulos and Halkidi (2014), the joint pdf is calculated using the multivariate Gaussian distribution assuming a time-invariant correlation matrix. Here, the correlation coefficient between the two sensors is updated in time using sample mean, variance and covariance (Papoulis and Pillai 2002).

Fig. 5 shows that using the copula-based detection significantly improves the local detection performance in nodes. Note that the copula-based detection outperforms the bivariate Gaussian method even in the scenario with Gaussian noise. The reason lies in estimating the correlation coefficient online which needs first to calculate the sample mean, variance and covariance while the copula-based detection needs just the sample mean. The other important superiority of the copula-based detection is its capability to handle non-Gaussian noises.

Any improvement in local detection performance improves the system-level detection performance if a monotone fusion rule is used (Viswanathan and Varshney 1997). We use a censoring technique in nodes in order to save energy. Each node sends no data to the FC unless it detects a fire occurrence, i.e. when its statistic is more than its threshold ($\Lambda_l > T_l$).

If a node detects a fire, it quantizes its statistic based on a four-level uniform quantization scheme, i.e. it sends its data during two bits. In the quantization strategy used in simulations, Λ_l is divided into four intervals between the two extreme conditions: (the highest temperature, the lowest humidity) and (the lowest temperature, the highest humidity). Here, the highest temperature is 80 °C and any temperature more than 80 °C is limited to it. Also, the lowest temperature is zero. In addition, μ_{FC} and η_{FC} are considered as the lowest temperature and the highest humidity, respectively.

The quantized data is used by the FC for weighting the decisions of sensors (Eq. 4). In fact, a modification of the counting rule (4) is used which has been referred to as the weighted decision fusion (WDF) in Javadi and Peiravi (2015) where its superiority compared to the counting rule has been shown. Using the WDF as the fusion rule, the decisions of the nodes in the vicinity of the fire are weighed more than the others.

As it is shown in Fig. 6, considering correlation in nodes results in the overall performance improvement, especially in low false alarm rates.

6 Conclusion

Immediate fire detection is crucial in environment surveillance in order to avoid vast losses. To have valid fire alarms, it is vital to design a detector with very low false alarm rates. Wireless sensor networks (WSN) are appropriate solutions in environment surveillance. In this study, an attempt was made to improve detection performance of an implemented fire detector WSN by considering the correlation among sensors connected to each network node. It was shown that considering the correlation between the measurements of the temperature and the relative humidity sensors by using copula functions when fire occurs would result in improvement of the overall performance of the detector network.

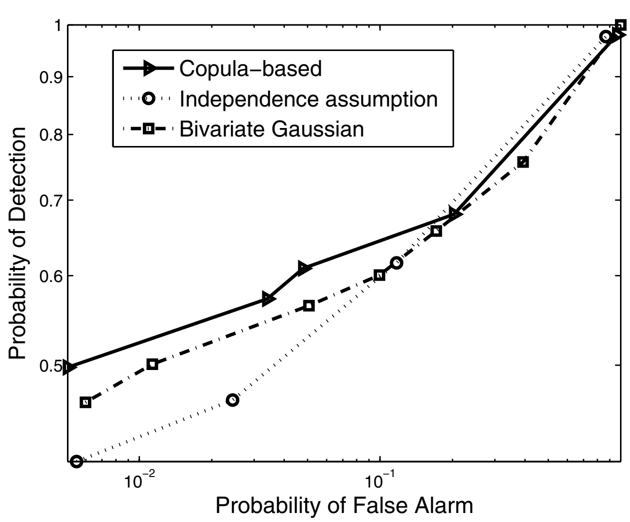

Fig. 6 The system Receiver Operating Characteristics (ROC) based on over 5000 Monte Carlo trials

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