A Multi-level Data Fusion Approach for Early Fire Detection

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Abstract—**Wireless Sensor Networks (WSN) allows large scale deployments for environmental monitoring applications especially in the Wildland Urban Interface (WUI) (i.e. in areas where forests and rural lands interface with homes, other buildings and infrastructures). In such areas early fire detection is of great importance as the consequences of a fire are catastrophic. Towards this direction the SCIER[1] project envisages the deployment of Wireless Sensor Networks at the WUI using a multi-level scheme of data fusion to enhance the performance of the early fire detection process.**

Fire detection; Sensor networks; Multilevel data fusion;Cusum; Evidence combination rules

I. Introduction

The term Wildland Urban Interface (WUI) is used to refer to all types of areas/zones where forests, water bodies, and rural lands interface with homes, other buildings and infrastructures, including first and secondary home areas, industrial areas and tourist developments [1]. In such areas fires are frequent due to their special nature; a fire could be the result either of human on one side of the zone, or could arrive from the other side (wildland). In such cases early detection leads to an efficient control of the fire and makes feasible the immediate evacuation of the entire area if this is considered necessary.

Prior research activities on fire detection and monitoring have been conducted. Most of them make use of temperature and humidity sensors, smoke detectors, infrared cameras, etc. In addition, aerial or satellite images are frequently used for outdoor fire detection and monitoring. In [2] a fire detection system is proposed based on multi-sensor technology and neural networks. The sensed data include environmental temperature, smoke density and CO density. In [3] and [4], authors present a system that is based on various types of sensors and use neural networks. However such systems require the use of training data and most of them are evaluated indoors where the weather conditions are fully controllable and, surely, completely different in comparison with those observed in a WUI. A system for wildfire monitoring using a wireless sensor network (WSN) that collects temperature relative humidity and barometric pressure is described in [5]. The authors in [6] and [7] propose systems based on infrared (IR) technology for the detection of fires. Furthermore, authors in [8] and [9] have proposed solutions in which sensors are deployed from an aircraft. Satellite based monitoring [10] is another method to detect forest fires but the scan period and the low resolution of satellite images make this method incapable for real-time detection.

The SCIER (Sensor & Computing Infrastructure for Environmental Risks) project designs, develops, and demonstrates an integrated system of sensors, networking and computing infrastructure for detecting, monitoring and predicting natural hazards (fires, etc.) at the WUI. In the case of fire detection one requires measurements from in-field sensors that are deployed in the area or out-field sensors which monitor the same area from a distance. In SCIER system temperature and humidity sensors (in-field) and vision sensors (out-of-field) are used. In the first level of fusion (data fusion) we adopt the cumulative sum technique for fusing data from in-field sensors and assigning a probability of fire occurrence to each of them. In the second level fusion (information fusion), probability values about fire events from the first level are combined through evidential theory (Dempster–Shafer) with probability values about fire events from the vision sensor. The adoption of a two-layer fusion process assists in the direction of reducing false alarm rates while satisfying the early fire detection requirement, contrary to the prior activities that use only one field sensor (in-field or out-of-field) rendering them vulnerable to false alarms

The rest of the paper is organized as follows: in Section 2 the SCIER architecture regarding the basic components is described. Section 3 discusses the fire detection process in SCIER based on multilevel data fusion and explains shortly how the results of such fusion process are used to estimate the evolution of the fire. Finally, in Section 4 conclusions are presented and open research issues are discussed.

II. SCIER System Architecture

Since an environmental hazard has occurred in the WUI region, SCIER provides the capabilities of detecting, monitoring and predicting its evolution. The platform is a complex system which integrates technologies and applies techniques from different scientific fields. It is customary that the architecture of such a large-scale integrated system is multi-layered, and each layer performs a specific set of activities. Neighbouring layers contribute to their common Interface so that all bilateral transactions are reliable and safe.

[1]SCIER (Sensor & Computing Infrastructure for Environmental Risks) is partially funded by the European Community through the FP6 IST Program.

In the SCIER case, we identify three (3) architectural layers: the *Sensing Subsystem (SS)*, the *Localized Alerting Subsystem (LAS)* and the *Computing Subsystem (CS)*.

A. Sensing Subsystem

The purpose of the SCIER sensing subsystem is the monitoring of the environmental parameters that are relevant to the assessment of a natural hazard. In the WUI two kinds of sensors are deployed: Citizen Owned Sensors (COS), installed by land/home owners in fixed and registered locations in private areas, and Publicly Owned Sensors (POS), installed by state authorities in fixed and known locations in public areas. The sensor nodes are energy efficient and form a multi-hop, self-organized, robust Wireless Sensor Network transmitting the raw measurements to a sink node via appropriate routing protocols.

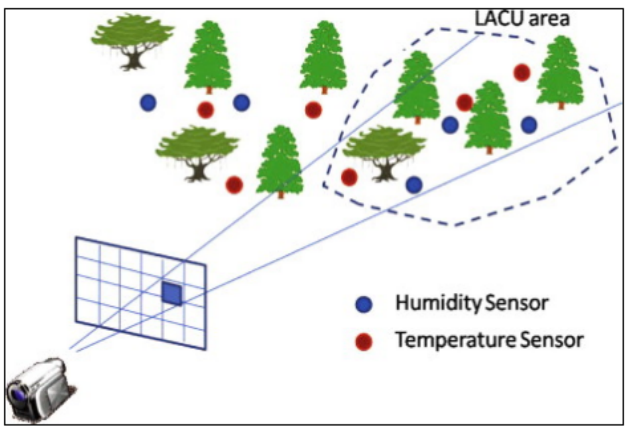

Figure 1. Distribution of SCIER nodes on the field.

In the SCIER system temperature, humidity sensors (in-field) and vision sensors (out-field) are used for fire detection. The latter are based on a high-dynamic range contrast camera in which the contrast representation of a scene can be used (through appropriate algorithms) to detect smoke or flames and estimate/generate a probability on this event. According to the luminance of the environment which depends on the time of the day the vision sensor which divides the scene into tiles, generates the appropriate probability for each tile. Smoke probability in the daylight and flame probability at night. Vision sensor nodes are fixed nodes, most likely installed on poles or citizens' homes. Figure 1 depicts the spatial distribution of the nodes in the field.

B. Localized Alerting Subsystem

LAS includes the Local Alerting Control Unit (LACU) which controls an area of deployed sensors and performs fusion algorithms for fire detection. LACU is a device which resides between the Computing Subsystem and the Sensing Subsystem as depicted in Figure 2. The basic components that comprise LACU and their role are described in the following paragraphs.

- *Communication proxy*, which is responsible for the communication between LACU and Computing Subsystem.
- *Sensor proxy*, which receives and stores readings transmitted by the sensors deployed in the monitored area.
- *Fusion component*, which assesses sensor data and determines if a fire outbreak occurs in the area. Furthermore, it estimates the exact location of the fire.
- *Alerting component*, which is triggered by Fusion Component and provides notifications to the Computing Subsystem when an emergency situation occurs (e.g fire).
- *Data Base*, which stores historical data, the identification of each sensor and its location as well as the readings arriving from the Sensor proxy.

The topology of the WSN controlled by a LACU plays an important role in the fusion process. The density of sensors depends on the area that is monitored and the desired accuracy of fire location estimation. A false alarm is the situation when the detection algorithm decides that there is a fire and actually there is not. It is clear that if we need a reasonable number of false alarms then the detection latency of the system increases (i.e. it is possible to not detect a fire). The false alarm rate is parameterized and it depends on the user requirements, on season of the year (e.g. summer) and on the risk factor of the monitored area.

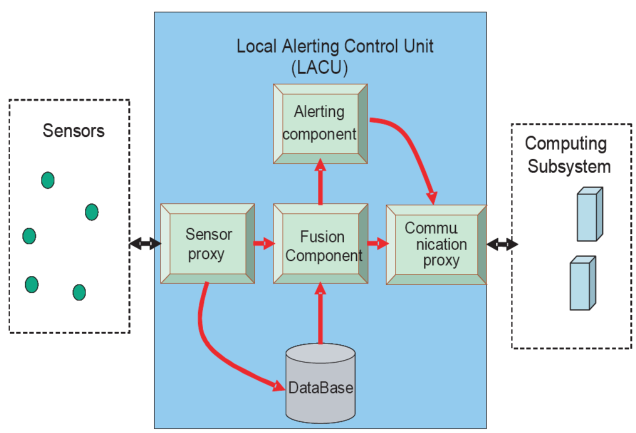

Figure 2. LACU architecture.

C. Computing Subsystem

The Computing Subsystem (CS) is largely based on a GIS and Grid computing infrastructure where the fused sensor information is stored, processed and visualized using additional weather data (e.g. wind speed and direction). For the detection phase of a phenomenon (e.g., fire) an information fusion process is adopted based on the evidential theory (Dempster–Shafer). Following the fusion process, multiple mathematical environmental models of different time scales are used in order to establish a highly accurate

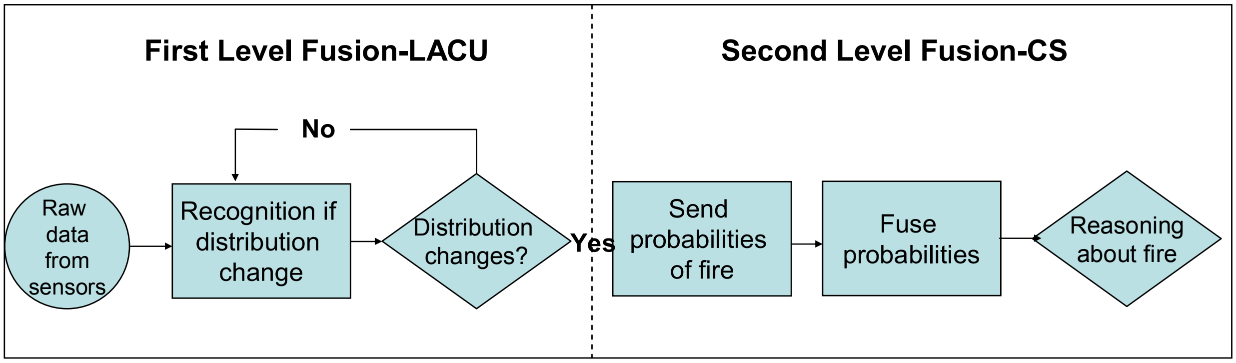

Figure 3. Multi-level fusion scheme adopted for fire detection.

tracking of the phenomenon (e.g. in the case of the fire the fire front evolution estimation). The output models may, in certain cases, re-feed the sensor infrastructure. Hence, the CS is capable of reconfiguring itself to adapt to the dynamics of the observed phenomenon resulting to the best possible monitoring.

The main functionalities of Computing Subsystem are:

- Collect and store sensor-measurements from the area of interest
- Perform data-fusion-algorithms to assess the level of risk
- Trigger a simulation in case of an alarm, i.e. retrieve geographical data from the GIS Database on the terrain layout of the area of interest.

III. Data Fusion And Evolution Estimation

In each LACU, readings from in-field sensors are constantly processed through a sensor data fusion procedure (first level fusion) in order to detect any significant change in the environmental state. For instance, consider the event in which the normal ambient temperature increases, in an abnormal way. This could indicate possible fire event. The system regularly monitors the data distribution that is generated over time. If a change in the data distribution is detected, this is reflected on a specific "metric". Such "metric" postulates a translation of the impact of the evidence to a certain amount of belief on a current hypothesis (the fire event hypothesis in our case). The probability is calculated for each sensor.

In an analogous data fusion procedure, for each out-of-field vision sensor, any significant change in the contrast or the luminance of the monitored scene is translated through specific algorithms to a probability of fire. Such probabilities from multiple sensors of different categories are fed to the information fusion algorithms (second level fusion) and are combined through the Dempster–Shafer theory in order to assume a safe decision about fire occurrence. Figure 3 depicts the whole work flow regarding the aspect of the fusion process in SCIER as it is discussed in the following sections.

A. *First level fusion*

Let $\{X_i\}$ denote a sequence of random variables, i.e., a sequence of independent measurements of a temperature sensor. We assume that X_i have density $f(x_i;\mu_0,\sigma)$ for i=1,…,τ-1 and density $f(x_i;\mu_F,\sigma)$ for $i\geq\tau$, where parameter μ_0 is known and, μ_F and σ are generally unknown. The time index τ signals the event in which a change in the distribution of the measurements occurs. In terms of the SCIER project, μ_0 denote the mean temperature value (in the no fire case) and depends on the hour of the date and the month of the year. It can be estimated from statistical data (stored in the database of LACU), empirical models, forecasting, or even the sensors themselves. In the last case measurements are recorded every T_0 (i.e., T_0=30 min). This time window length is in general variable and it is advisable to decrease it during daily periods that are characterized by large temperature differences, i.e., from 5:00 am to 12:00 am. Thus, $\mu_0(h)$ can be obtained by a weighted average of all aforementioned estimation techniques, such as

$$\mu_0(h) = w_1\mu^e(h) + w_2\mu^h(h) + w_3\mu^f(h) + w_4\mu^m(h)$$
$$\sum_i w_i = 1, w_4 > w_3 > w_2 > w_1 \quad (1)$$

where the superscripts *e, h, f* and *m* denote empirical, historical, forecasting and measured estimates respectively. For the empirical estimation of temperature Walters' model [11] provides an "average unit curve" of temperature according to the time of the day.

One of the most promising algorithms to sequentially detect a distribution change is the Page's CUSUM test [12]. For instance, if the parameter of interest, which indicates a possible fire event, is the mean value μ_0, we can monitor the partial sums $S_n - \min_{1\leq k\leq k} S_k, n = 1,2,...$ where

$S_n = \sum_{i=1}^{n} X_i$ and conclude that a change from the initial μ_0 mean value to μ_F occurs at time n. Gombay [13] adapted Page's CUSUM test for change detection in the presence of nuisance parameters (the variance σ^2) which in the case of fire detection is described analytically in [14].

Sensors that are capable of sensing humidity are also used for fire detection. In the case of fire the relative humidity decreases contrary to the temperature that increases. The same techniques of change detection can be applied also for such sensors. In this case μ_0 denotes the ambient relative humidity which can be calculated in an analogous method as in (1).

After the occurrence of a fire event we can proceed to the formation of the basic probability assignments (BPA). There are several ways to assign BPA according to the sensors' measurements (temperature, humidity, etc.). One way is to use the likelihood scores for each sensor node.

$$m(fire) = \frac{f(x_i;\mu_F,\sigma)}{f(x_i;\mu_F,\sigma) + f(x_i;\mu_0,\sigma)} \tag{2}$$

The μ_F can be set equal to $\mu_0+\mu_d$, where μ_d is a sufficiently large value that exceeds possible temperature variations within a corresponding time window T_0. These variations can be obtained through historical data, daily temperature patterns, etc. Alternatively, we may use an increasing function $g(\cdot)$ that maps the interval $[\mu_0,\mu_0+\mu_d]$ to the interval [0,1].

B. *Second level fusion*

In the second level fusion process vision sensor (camera) data and data coming from LACU are combined. Each single fusion process will be based on data for a single camera tile together with data from the sensors that this camera tile oversees. In those cases where a camera tile does not oversee any sensor(s), or a/any sensor(s) is/are not overseen by a camera, a degenerate fusion process will be carried out taking into account the probabilities of a single camera tile or any sensor(s) respectively.

Probabilities are combined through Dempster–Shafer (DS) evidential theory [15]. Consider the mass $m_i(U)$ that is the current probability of occurrence of a piece of evidence in U for the S_i expert, i.e., temperature or vision sensor. Then the combination of the decisions of experts S_i and S_j is provided by:

$$m_{i,j}(U) = (m_i \oplus m_j) = \frac{1}{1-K} \sum_{B \cap C = U \neq 0} m_i(B) m_j(C) \tag{3}$$

where

$$K = \sum_{B \cap C = 0} m_i(B) m_j(C) \tag{4}$$

The K value represents a measure of the amount of conflict between the two mass sets. In DS process for each sensor we need the BPAs *m(F)*, *m(no - F)* and the unsigned probability mass *m(F U no - F)*. The mass *m(F)* represents the belief in fire detection, *m(no - F)* the belief in the no–fire case and *m(F U no - F)* represents the uncertainty of the sensor. For fusing the probabilities of three sensors, one has first to combine two sensors to obtain $m_{12}(F)$, $m_{12}(no - F)$ and $m_{12}(F\ U\ no - F)$ and then use Dempster-Shafer rule to obtain $m_{123}(F)$, $m_{123}(no - F)$ and $m_{123}(F\ U\ no - F)$. Once exhausting the sensors we are left with the basic probability masses:

$m_{123\ldots M}(F)$, $m_{123\ldots M}(noF)$ and $m_{123\ldots M}(F\ U\ no - F)$

For final detection purposes we can use either the support $m_{123\ldots M}(F)$ and compare it to a threshold t, or the plausibility $m_{123\ldots M}(F) + m_{123\ldots M}(F\ U\ no - F)$ and compare it to a threshold t, or even the average of the these two.

C. *Fire front evolution*

The fusion algorithms described, confirm whether an event constitutes a real threat or it is a false alarm. In the former case the SCIER Computing Subsystem initiates a simulation in the Grid infrastructure consisting of several parallel runs. Each run is based on a different set of input parameters and computes the expected evolution of the fire front line for up to 180 minutes after fire detection. Feeding the model with information about the topography, moisture content, type of the surface fuel and dynamic environmental parameters such as the wind, the evolution can be specified accurately. The aforementioned process is described in detail in [16]. The visualization of a typical scenario regarding the fire front evolution is depicted in Figure 4.

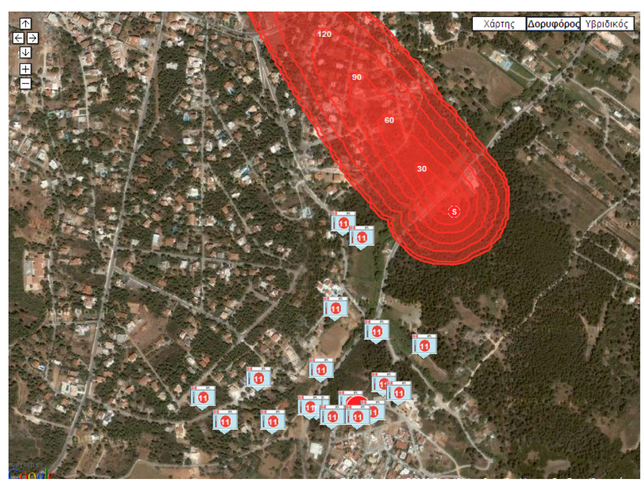

Figure 4. Fire front evolution estimation.

IV. CONLUSIONS AND FURTHER WORK

In this paper a fire detection mechanism is proposed, based on multi-level data fusion. The data are obtained using a wireless network of environmental (temperature and humidity) sensors scattered at the supervising WUI area and a vision sensor that monitors the same geographical area. To cope with all these different types of sensors and deliver alarms with increased accuracy and confidence a layered fusion scheme has been adopted. Different sensor feeds are processed in the two layers of the fusion scheme thus improving the reliability of the system in detecting fires. On the lower layer, the statistical behavior of sensor data is constantly assessed. On the higher layer, D-S theory of evidence is adopted in order to mix the indications coming from the lower layer and the out-of-field vision sensors. As a future work, we propose the enhancement of the implemented algorithms with alternative combination rules, and the adoption of the Fuzzy Set theory to deal with uncertainty, imprecision and incompleteness of the underlying data.

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