Multi-Modal Evidence Filtering in Wireless Sensor Networks

Dilusha Madushani Weeraddana

(138018 E)

Degree of Master of Philosophy

Department of Electronic and Telecommunication Engineering

University of Moratuwa
Sri Lanka

June 2015

Abstract

A novel framework named ***Dempster-Shafer Information Filtering*** for information processing in Distributed Sensor Networks (DSNs) is presented. Moreover, distributed algorithms to implement spatio-temporal filtering applications in grid sensor networks are presented within the context of the framework. The framework facilitates processing multi-modality sensor data with a high noise level. Moreover, we compare intuitively appealing results against Dempster-Shafer fusion to grant further credence to the proposed framework.

The concept of the proposed framework is based on the belief notions in Dempster-Shafer (DS) evidence theory. It enables one to directly process temporally and spatially distributed multi-modality sensor data to extract meaning buried in the noise clutter. Certain facts on filter parameter's selection impose several challenges in the design of the Information Filter. This is analysed using a fire propagation scenario when high noise is present in the sensed data. Information bandwidth and the sluggishness of the filter are traded-off to minimise the effect of the noise in the output evidence signal.

From the application point of view, we address a Wireless Sensor Network (WSN) deployed in a multi-stoery building which can be effectively used to convey information to relevant parties (firefighters in their rescue operations) during an emergency situation. Therefore, a fire propagation scenario is simulated to illustrate the applications and justify the proposed framework.

Acknowledgements

First and foremost, I would like to extend my deepest gratitude to my supervisors Prof. S. A. D Dias, Dr. E. C. Kulasekere and Prof. K. S. Walgama for their continuous guidance, advice and support throughout my research.

I wish to extend my earnest gratitude to members of my project panel Eng. K. Samarasinghe, Dr. K. C. B. Wavegedara, and Dr. D. Bandara for their valuable comments on my research work.

I also thank my dear friends and colleagues in department of Electronic and Telecommunication Engineering, University of Moratuwa for their assistance and encouragement. I would also like to thank National research Council, Sri Lanka for funding my research through grant 11-113 for the entire duration to make it a success

Last but not least I would like to thank Dialog-University of Moratuwa mobile communications research laboratory for partially supporting my studentship.

I declare that this is my own work and this thesis/dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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Chapter 1

Introduction

Sensors attached to communication interfaces have been in use for many years. However recently, there has been a renewed research interest on *networked* sensors which are able to communicate among themselves using a wireless communication protocol (Zigbee etc.) [1].

Wireless sensor networks (WSNs) enable us to gather information about specified regions or tasks. The emergence of Wireless Sensor Networks shed light on creation of new smart sensor systems, which can be useful to enhance the quality of human lives. WSNs are used in variety of applications, such as medicine, urban monitoring, military, traffic control, environment and habitat monitoring, energy management, green buildings, sick building monitoring, emergency management etc. [2] [3] [4][5].

Among other advantages of WSNs, autonomy has gained more attraction. The microprocessor of the nodes automatically initializes communication with every other node in range in the network and creates an ad hoc mesh network for exchanging information with the gateway node. This negates the need for costly wiring between nodes which limits their mobility. Therefore this allows nodes to be deployed in almost any location.

An addition to monitoring, computing, communicating and actuating capabilities, with the added microcomputer processing power, handling of multi-modality sensor systems, analog and digital ports, transceivers and available memory, WSNs have the capabilities to self-organize [6], self localize [7], communicate and make decisions [8] in the deployed area.

However many WSNs use inexpensive sensors to compromise between cost and performance. This causes the sensor measurements to suffer from several problems such as outliers and missing information. In addition to that WSNs are subject to systematic errors (i.e. aging of the sensor) and random errors (noise). The random noise is hard to recover from calibration. This include random environmental effects, hardware inaccuracies etc. Especially during an emergency high uncertainty is added to the evidences due to communication link failures, sensor node failures etc. Moreover, in WSNs, the environments under observation is inherently uncertain. In most of the cases the prior knowledge or conditional probabilities are not available. Therefore improper initial assumptions can weaken the integrity and the reliability of the decision making process (i.e. detecting emergencies while reducing the false alarms) [9].

The reliability of information gathered from sensor networks are extremely important since important actions are usually taken based upon these sensed information. Hence, the cost of any unreliable information can be very significant specially when it is used for critical decisions (firefighters in their rescue operations) or activation of actuators. All the problems mentioned above in WSNs seriously impact the information obtained from such networks. Therefore the use of multiple sensing modalities and fusion of gathered evidences temporally and spatially can significantly enhance the robustness and the accuracy of the decision making process in such environments [10].

1.1 Decision Making in Sensor Networks

The decisions made based on the fused information range from estimating location or velocity of an object, identifying and distinguishing different states of environments (severity state of an emergency) as well as detecting the presence or absence of events (emergency detection, high energy consumption in a building).

Bayesian inference theory is widely used as a sensor fusion technique. It decides on the validity of a proposed hypothesis based on probabilities. Bayes theorem [11] is used to update the probability of a hypothesis, with the arrival of new evidence. However Bayesian theory requires *prior* probabilities of the hypothesis. When no such knowledge is available the *principle of indifference* is used by assigning equal probabilities to all the propositions.

Kalman Filters [12], Monte-Carlo Filters [13], Particle Filters [14] and Bayesian Filters [15] are the most popular other sensor fusion methods derived from Bayesian theory. The Kalman Filter yields the least square error. It deals with fusing N independent sensors where each sensor has a known measurement distribution. The filter produces the optimal fusion method to combine outputs of all these sensors such that the mean square error is minimized. The Kalman Filter is developed based on training data. The training data is prior measurements obtained by the sensors.

However the situation we consider here is different. The sensor data contains a high degree of inaccuracy and uncertainty due to the nature of the system and the application. In most cases, we do not have physical access to nodes to sensor nodes after initial deployment. Moreover, prior information, conditional probability, joint probability distributions are not available. There are many advantages of using Dempster-Shafer (DS) theory in such scenarios. Most importantly, the DS method relaxes the Bayesian method's restriction on mutually exclusive hypotheses as if no prior information is available we can avoid assigning probabilities to singleton propositions.

The Demspter-Shafer theory suffers from several drawbacks. The Demspter-Shafer Evidence Updating method presented in [16] and [8] is one of the proposed methods to overcome certain drawbacks in the original DS evidence theory. During the evidence combination, above method updates the existing knowledge base with the new evidence while taking into account the inertia and integrity of its already available knowledge. Furthermore it is capable of fusion over nonidentical DS Frame of Discernments (FODs). However estimation of time varying environments is not addressed in the above work.

Evidence Filtering framework reported in [17] is capable of fusing multi-modality evidences to directly infer on frequency domain, which is derived from DS framework and Evidence Updating method [8]. Recursive and non recursive linear time invariant Evidence Filtering frameworks are presented in [17] [18]. Therefore the properties in the DS theory and the Evidence Filtering are highly important in our context.

However the time domain analysis is not done in the Evidence Filtering framework, and the noise buried in the clutter has never been addressed. In this thesis, our main focus is to address above two aspects and facilitate a node to fuse information internally over time while enable each node to exchange their knowledge base with peer nodes in order to develop more accurate global knowledge about the scenario (spatio-temporal filtering).

1.2 Self-Organization of Sensor Nodes

WSNs may consist of hundreds, thousands or even millions of low power inexpensive sensor nodes that may be placed either regularly or irregularly. Moreover, the ad-hoc deployment of the sensor nodes, prevent pre-planning of the network organization. Therefore the network needs to self-organize each node to interact with the environment to monitor or sense physical parameters and transmit data to a central location. Hence it is an essential requirement of WSNs to be self-organized.

Self organization process involves the decomposition of the network into connected clusters or groups. In clustering, selection of Cluster Head, Cluster Head density and Re-clustering are the most critical aspects to be considered. In this thesis we restrict our scope to energy based clustering algorithms.

LEACH [19] is the most popular and simplest energy efficient adaptive clustering protocol proposed for periodical data gathering applications in WSNs. SEP [20] was introduced as an extension to LEACH. Both are simple, do not need large overheads and the nodes make decisions. However they randomly select few sensor nodes as Cluster Heads (CH) which leads to non uniform cluster formation. HEED [21] periodically selects CHs according to their residual energy to avoid the non uniform cluster distribution, but is based on a complex weight based cluster setup procedure. EDAC [22] has an energy based CH selection and rotation mechanisms. In EDAC, cluster boundaries do not change with time. EDCR [6] avoids most of the problems in previously mentioned clustering algorithms. This uses the residual energy of sensor nodes for selection and rotation of CHs.

However current clustering algorithms mainly focus on energy usage of the node (as mentioned above) and some other parameters such as bandwidth and packet synchronization. Unfortunately there is a lack of coherence in research especially when it comes to self-organizing algorithms for emergency response. In this thesis, we propose an optimized self-organizing algorithm named ***Severity based Clustering Algorithm for Emergency (SCAE)*** to prolong the network lifespan during an emergency.

1.3 Emergency Response and Management

Emergencies such as fire, gas leakages, earthquakes, tsunamis, terrorist attacks bring long lasting suffering to the affected society. According to the statistics of

New York 9/11 incident, approximately 400 firefighters died during the rescue operation and the total death was estimated to be over 6000. Due to the severe loss of human lives and valuable assets, there is an increasing interest in proposing improvements in the ability to respond to emergencies with the aim of minimizing the severity of the impact caused by an emergency.

Recently, wireless sensor networks (WSNs) raise many exciting opportunities to minimize the impacts caused by emergencies [23] [24] [25] [26].

CodeBlue [24] is a protocol and a software framework which could integrate devices such as wearable vital sign sensors, handheld computers, and location-tracking tags into disaster response scenarios. This allows wireless monitoring and tracking of both patients (victims) and first responders (firefighters).

The work reported in [25] proposes a high-level architecture of the system that is capable of deploying the human computer interfaces suitable for supporting various firefighter job roles during a fire Emergency Response.

1.3.1 Challenges in Emergency Response

The nature of an emergency is highly dynamic and demanding. Real-time data retrieval, processing and management is required.

The identified challenges in emergency response and management are,

- Highly dynamic and demanding environments
- Noise added to the sensor data
- Real time information retrieval from various sources (i.e. WSN), processing, and managing information dynamically.
- Need of separate robust algorithms for victim navigation and first responder navigation.
- First responder and victim navigation algorithms require different types of information. Differentiate the gathered information among different types navigation algorithms is another challenge.
- WSN deployed inside the building need an efficient communication protocol to optimize the energy usage, communication delay, packet retransmission, etc.

- First responders may add stationary and mobile sensor nodes (sensors attached to firefighters) to the WSN. Integrating and tracking the newly added nodes is also a challenge.

- Addition to the information from the WSN, information about environmental conditions of the surrounding region i.e. wind speed, land marks should be acquired from separate data sources.

- Knowledge sharing mechanism among the WSN and other data sources.

To cater to all the above listed issues in one architecture is one of the major challenges we address in this thesis. Additionally we address localization, self-organization of the network and navigation algorithms to propose a WSN architecture for emergency response.

Chapter 2

Preliminaries

2.1 Dempster-Shafer Theory

Dempster-Shafer (DS) theory [27] can be interpreted as a generalization of Bayesian probability theory. The probabilities are assigned to sets as opposed to mutually exclusive singletons. The underlying notions and the definitions are briefly discussed in this section.

Let $\Theta = \{\theta_1, \theta_2, ...\theta_n\}$ denote the total set of mutually exclusive and exhaustive propositions referred as the frame of discernment (FOD). Elements in the power set form all propositions of interest. A proposition is referred to as a singleton and represents the lowest level of discernible information. Other propositions are referred to as composites, e.g.,$(\theta_1, \theta_2) \subseteq \Theta$. A-B denotes all propositions in A after removal of those propositions that may imply B.

There are three important functions in DS theory, the basic probability assignment function (bpa or m), the Belief function (Bel), and the Plausibility function (Pl).

Definition 1

The bpa (m) defines a mapping of the power set to the interval between 0 and 1, where the bpa of the null set is 0, and the summation of the bpas of all the subsets of the power set is equals to 1. i.e;
$m : 2^{\theta} \Rightarrow [0, 1]$
$m(\phi) = 0$; and $\Sigma_{A \subseteq \Theta} m(A) = 1$

The mass of a composite proposition is free to move into its singletons. This is how the notion of ignorance, the main feature in DS theory is modeled.

A proposition that possesses a nonzero mass is referred to as a focal element. The set of focal elements is denoted by $\Im$ and the triple $\{\Theta, \Im, m\}$ is referred to as the body of evidence (BOE).

Definition 2

The upper and lower bounds of an interval is defined from the basic probability assignment (*bpa*). The lower bound is referred to as Belief (Bel) for a set A defined as the sum of all the basic probability assignments of the proper subsets (B) of the set of interest (A) (B $\subseteq$ A).
The upper bound Plausibility (Pl), is the sum of all the basic probability assignments of the sets (B) that intersect the set of interest (A) (B $\cap$ A $\neq \emptyset$).
Given a BOE $\{\Theta, \Im, m\}, m(A) \subseteq \Theta$

$$Bel(A) = \Sigma_{B \subseteq A} m(B) \tag{2.1}$$

$$Pl(A) = 1 - Bel(\bar{A}) = \Sigma_{B \cap A \neq \emptyset} m(B) \tag{2.2}$$

Definition 3

Dempster's rule combines multiple evidence functions through their basic probability assignments (m). These belief functions are defined on the same frame of discernment (FOD) based on independent arguments or bodies of evidence (BOE). Note that Dempster's rule of combination is purely a conjunctive operation (AND).

$$m(A)_\Theta = \frac{\Sigma_{C,D:C \cap D = A} m(C)_{\theta 1} m(D)_{\theta 2}}{K} \tag{2.3}$$

where $K = (1 - \Sigma_{C,D:C \cap D = \phi} m(C)_{\theta 1} m(D)_{\theta 2}), \forall A \subseteq \Theta$

2.2 Evidence Updating

2.2.1 Combination of Evidences via Evidence Conditioning

The work in [16] [8] [28] present an evidence updating strategy that addresses several major drawbacks in the Dempster's evidence combination function. It allows one to accommodate the inertia of available evidence and the reliability of sensors during combination of existing evidence in a node with incoming new evidence.

Moreover, evidence combination using different FOD s is possible in this method [8]. This overcomes the FOD restriction in the original Dempster-Shafer theory.

Here for simplicity identical FOD case is presented. (Evidence Filtering considers identical FOD case)

Definition 4 Consider BOEs $\{\Theta, \mathcal{F}_1, m_1\}, \{\Theta, \mathcal{F}_2, m_2\}$ and given $A = \mathcal{F}_2$, then the updated belief and plausibility for an arbitrary hypothesis B would be,

$$Bel(B)_1(k+1) = \alpha_k Bel(B)_1(k) + \beta_k Bel(B|A)_2(k) \tag{2.4}$$

$$Pl(B)_1(k+1) = \alpha_k Pl(B)_1(k) + \beta_k Pl(B|A)_2(k) \tag{2.5}$$

$\alpha_k, \beta_k \geq 0; \alpha_k + \beta_k = 1$

The condition in the above definition is the Fagin-Halpern conditional [29] which can be considered as a more natural extension of the Bayesian conditional notions.

In a distributed, multi-modality sensing environment, it is possible to have different conditioning events A depending on the expertise of each node.

$Bel(B|A)(k)$ captures the incoming evidence conditioned to A, while $Bel(B)(k)$ is the already available evidence. Then $Bel(B)(k+1)$ denotes the updated belief.

2.3 Evidence Filtering

2.3.1 Fundamental of Evidence Filtering

Evidence Filtering (EF) is based on conditional belief notions [29] in Dempster-Shafer evidence theory to directly process temporally and spatially distributed sensor data and infer on the frequency characteristics of events of interest. This is based on the evidence updating strategy [8] introduced in 2006 to minimize the drawbacks associated in DS evidence combination rule Definition 2.1. Recursive and non recursive linear time invariant Evidence Filtering frameworks are presented in [17] [18].

By giving additional dimensions to existing evidence combination (sensor fusion) methods via ordering the incoming evidences temporally, spatially would reveal certain information hidden in the raw sensor data [30].

Some of the identified facts in the existing EF will be discussed in the next sections.

According to the evidence updating method, a knowledge base should only consider the portion of the incoming evidence that it is capable of discerning itself. Lets consider that a node with a knowledge base denoted by the BOE $\{\Theta, \Im_1, m_1\}$ desires to update itself using new incoming evidence arriving from another node denoted by the BOE $\{\Theta, \Im_2, m_2\}$. Which is conditional to the occurrence of event A $\subset \Theta$. Then the current knowledge base available in the first node can be updated via

$$Bel(B)_1(k+1) = \alpha Bel(B)_1(k) + \beta Bel(B|A)_2(k) \tag{2.6}$$

$$Pl(B)_1(k+1) = \alpha Pl(B)_1(k) + \beta Pl(B|A)_2(k) \tag{2.7}$$

where $\alpha, \beta \geq 0$ and $\alpha + \beta = 1$.

Hence the impulse response and the transfer function can be given as below;

$$h(n) = \beta \alpha^n \tag{2.8}$$

$$H(z) = \frac{\beta . z^{-1}}{1 - \alpha . z^{-1}} \tag{2.9}$$

The index k in equation (2.6, 2.7) denotes the temporal ordering of the evidences and represents a discrete time index $t = kT$, where T denotes the sampling time of the evidence at each node and t denotes the continuous time. The most general form of equation 2.6 can be stated as the N^{th} order difference equation

$$Bel(B)(k) \quad = \quad \Sigma_{i=1}^{N}\alpha_i Bel(B)(k \ - \ i) \ + \ \Sigma_{i=1}^{N}\beta_i Bel(B|A)(k-i) \quad (2.10)$$

where $\alpha_i, \beta_i \geq 0$ and $\Sigma_{i=1}^{N}\alpha_i + \Sigma_{i=1}^{N}\beta_i = 1$.

The above constraints on the filter coefficients are needed to ensure that the updated belief and plausibility constitute valid belief functions and plausibility functions according to Definition 2.1.

Filter in equation (2.10) corresponds to the transfer function of the N^{th} order recursive filter.

$$H_B(z) = \frac{\Sigma_{j=1}^{N}\beta_j z^{-j}}{1 - \Sigma_{i=1}^{N}\alpha_i z^{-i}} \quad (2.11)$$

$Bel(B|A)(k)$ captures the incoming evidence conditioned on A, while $Bel(B)(k)$ is the already available evidence. $Bel(B)(k+1)$ denotes the updated belief.

In a multiple modality sensing environment, it is possible to have different conditioning events A depending on the expertise of each node. Note that similar notions hold for the plausibility (Pl).

2.3.2 Identified Facts regarding the Evidence Filter

Time Domain Analysis

The Evidence Filtering framework was analysed in the frequency domain. The time domain analysis is not done in the Evidence Filtering framework. In this research we focus on developing an Evidence Filter in the time domain. The information ordered temporally reveals certain important information on the environment under observation.

Spatio-Temporal Evidence Filtering

The Spatio-Temporal Evidence Filtering is not completely addressed in the Evidence Filtering framework. The Fornasini-Marchesini model based 2 dimensional (1-D in space and time) system approach is presented in the work reported in [31] .

In this research we will be presenting higher order Spatio-Temporal Evidence Filters based on grid sensor networks. Each node communicates with peer nodes to exchange their knowledge bases to obtain global knowledge about the scenario.

Noise Buried in the Information Clutter

The noise buried in the clutter has never been addressed in the Evidence Filter. One of our main objectives is to extract the information buried in the noise clutter.

Linearity of the Evidence Filter

N^{th} order FIR Evidence filter

$$Bel(B)(n) = \Sigma_{i=1}^{i=N} \beta_i Bel(B|A)(n-i) \tag{2.12}$$

$$0 \leq Bel(B) \leqslant 1 \tag{2.13}$$

$$0 \leq Bel(B|A) \leqslant 1 \tag{2.14}$$

$$\Sigma_{i=1}^{i=N} \beta_i = 1 \tag{2.15}$$

Applying superposition principle;
RHS :

$$\Sigma_{i=1}^{i=N} \beta_i (a_1.Bel(B|A)_1(n - i) + a_2.Bel(B|A)_2(n - i)) \tag{2.16}$$

LHS :

$$a_1 \Sigma_{i=1}^{i=N} \beta_i Bel(B|A)_1(n-i) + a_2 \Sigma_{i=1}^{i=N} \beta_i Bel(B|A)_2(n-i) = a_1 Bel(B)_1(n) + a_2 Bel(B)_2(n) \tag{2.17}$$

Here a_1, a_2 are constants. Therefore, FIR Evidence Filter is a linear discrete filter.

N^{th} order IIR Evidence filter

$$Bel(B)(n) = \Sigma_{i=1}^{i=N} \alpha_i Bel(B)(n-i) + \Sigma_{i=1}^{i=N} \beta_i Bel(B|A)(n-i) \tag{2.18}$$

take the first order filter N=1
at n=1

$$Bel(B)(1) = \alpha_1 Bel(B)(0) + \beta_1 Bel(B|A)(0) \tag{2.19}$$

Applying the superposition principle
RHS :

$$\begin{multline} \alpha_1 Bel(B)(o) + \beta_1(a_1.Bel(B|A)_1(0) + a_2.Bel(B|A)_2(0)) = \\ \alpha_1 Bel(B)(o) + a_1\beta_1 Bel(B|A)_1(0) + a_2\beta_1 Bel(B|A)_2(0) \end{multline} \tag{2.20}$$

LHS :

$$a_1 Bel(B)_1(1) + a_2 Bel(B)_2(1) \tag{2.21}$$

if $Bel(B)(0) = 0$; RHS=LHS ;

Therefore IIR Evidence Filter follows superposition principle iff $Bel(B)(0) = 0$, this is true for $N \geq 1$ (a_1, a_2 are constants).

Dempster-Shafer Theroy and Evidence Filtering for Sensor Fusion in Emergency Situations

Emergency situations are highly dynamic where the state of the environment may change rapidly. Moreover, accuracy of the information is very important (i.e. reduce false alarm rate).

Bayesian filtering, Kalman filtering, Fuzzy theory, Neural networks, Dempster-Shafer (DS) formalism are widely used as sensor fusion, information fusion techniques in past decades.

However the advantages in Dempster-Shafer theoretic methods become evident when the assumptions typical of a Bayesian approach (e.g., conditional independence, availability of prior knowledge, joint probability distribution etc.) are difficult to justify [32]. In WSN applications such as emergency situations could gain more advantages of using Dempster-Shafer theory as it relaxes certain restrictions in Bayesian theory. For an example, the Bayesian method has a restriction on mutually exclusive hypotheses. This is relaxed in DS theory as masses can be assigned to composites propositions. This is highly useful in a multi-modality sensor network where the uncertainty of all possible (and previously unknown) events need to be properly quantified.

Evidence Filtering is an effective sensor fusion approach developed to deal with dynamic environments. It is facilitated with all the advantages of Dempster-Shafer formalism. Moreover, it overcomes some of the drawbacks associated with DS theory. Therefore it is a good candidate to address the challenges in highly dynamic environments such as emergency situations (see section 1.3.1).

Chapter 3

Analysis of Evidence Filtering in the Time Domain

The main objective of this chapter is to analyse the existing Evidence Filter in the time domain. A fire propagation scenario is simulated using three types of sensor modalities. Moreover, we will be addressing issues in the existing LTI Evidence Filter. Finally a simple Event Triggered Linear Time Varying Evidence Filter is proposed.

3.1 Construction of the Evidence Table

Lets consider a fire propagation in a particular building. We restrict our view on a knowledge base of one sensor node, three sensors are embedded in the sensor node to sense temperature, smoke and flame intensity of the fire.

Fire propagation is observed over 30 minutes to detect its severity variation over time. The sensor signals are sampled at a regular interval of 5 seconds ($T_s = 5sec$) and are mapped them to DS belief values. The prior information on the underlying sensor data distributions are not available.
We followed the procedure outlined below to map sensor data to DS beliefs:
The full range of sensor output signals are normalized to a scale of [0 1].

Table 3.1: Evidence Table

Proposition(B)	Mass(B)	Belief(B)	Plausibility(B)
Fire	m_f	m_f	$m_f + m_{f,n}$
No Fire	m_n	m_n	$m_n + m_{f,n}$
Fire,No Fire	$m_{f,n}$	$m_{f,n} + m_f + m_n$	$m_{f,n} + m_f + m_n$

$X_{temperature}(t) = \frac{T(t)-T_{room}}{MaxT-T_{room}}$
$X_{smoke}(t) = \frac{S(t)}{MaxS}$
$X_{colour}(t) = \frac{C(t)-C_{room}}{MaxC-C_{room}}$
T(t)= temperature with time
S(t)= smoke level with time
C(t)= colour level with time
T_{room}= room temperature
C_{room}= colour level when there is no fire
MaxT= maximum temperature
MaxS= maximum smoke level
MaxC= maximum colour level
$X_{tem}(t)$= normalized temperature with time
$X_{smoke}(t)$= normalized smoke with time
$X_{colour}(t)$= normalized colour with time

Average value (avg) of all three normalized sensor outputs are taken at the each time instant and the masses are assigned to the $DS\ FOD$={normal,fire} according to the normalized average function.

{m(normal),m(fire),m(normal,fire)}={1,0,0} if avg=[0.0 0.02)
{m(normal),m(fire),m(normal,fire)}={(1-avg),0,avg} if avg=[0.02 0.1)
{m(normal),m(fire),m(normal,fire)}={0,avg,(1-avg)} if avg=[0.1 0.5)
{m(normal),m(fire),m(normal,fire)}={0,avg,(1-avg)} if avg=[0.5 1.0]

At each time instant masses are generated from three sensors and the DS evidence table is updated. According to the masses generated from the average function, the belief and plausibility values are calculated and the complete evidence table is constructed as shown in Table 3.1.

Note that the room conditions (no fire) should be known and assigned prior to construction of the Evidence Signals.

3.2 Evidence Filter Design and Results

In this section the existing Evidence Filter is simulated and analyzed in the time domain.

The interested hypothesis in the fire propagation scenario here is taken as 'fire'. Then the evidence signal will be $Bel(fire)$. N^{th} order Evidence Filter

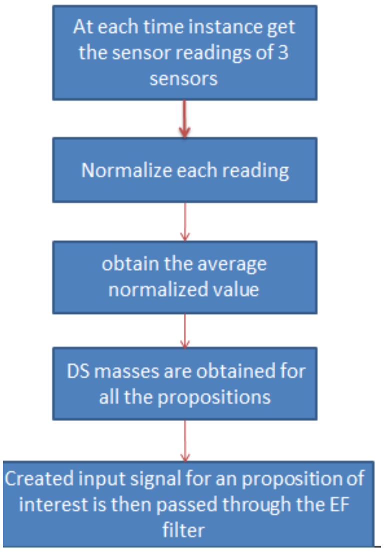


Fig. 3.1: Simulation steps

difference equation for our scenario is as below,

$$Bel(B)_1(k+1) = \alpha Bel(B)_1(k) + \beta Bel(B|A)_2(k) \tag{3.1}$$

$$Bel(fire)(k) = \Sigma_{i=1}^{N} \alpha_i Bel(fire)(k-i) + \Sigma_{i=1}^{N} \beta_i Bel(fire|\Theta)(k-i) \tag{3.2}$$

Here we take $A = FOD$, This can be changed to another subset of FOD to refine the results further. Figure 3.2 shows the artificially generated data over 30 minutes. Since the sampling time is 5 seconds, first 60 samples (5 minutes) is modeled as the no fire condition. A fire starts and propagates in the next 25 minutes. Simulation steps are shown in Figure 3.1.

3.2.1 Results Analysis

Figure 3.2 shows the artificial sensor data generated for the fire scenario for temperature, smoke and colour. The DS belief values for each hypothesis are shown in Figure 3.3. We can clearly observe the belief for 'no fire'(normal) is high in the first one minute while belief for 'fire'is low. On the contrary $Bel(normal)$ gradually declines and eventually becomes nearly zero once the fire severity increases with time. $Bel(fire)$ follows the opposite behaviour to $Bel(normal)$ and gradually increases its DS belief value and finally reaches the highest value of '1'.

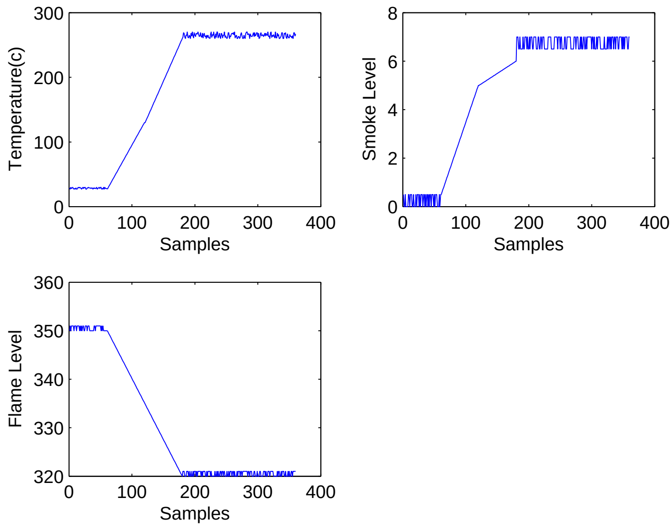


Fig. 3.2: Generated artificial data for 30min, each sensor data follows different function

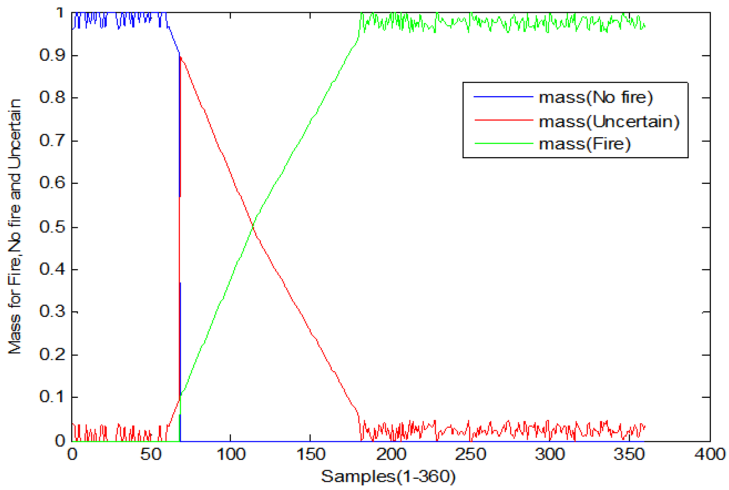


Fig. 3.3: Belief values for fire (green), normal (blue), uncertainty (red)

Figure 3.4 illustrates the output Evidence Signal of the first order Evidence Filter. This clearly illustrates how the severity level of fire changes over time based on only three sensor modalities.

3.3 Artifact Modelling in Linear Time Invariant Evidence Filtering

Artifacts are common in sensor networks. Due to the external environment, hardware/software imperfections sudden artifacts may occur in sensor data. In this section we try to eliminate sudden artifacts from the fused sensor data.

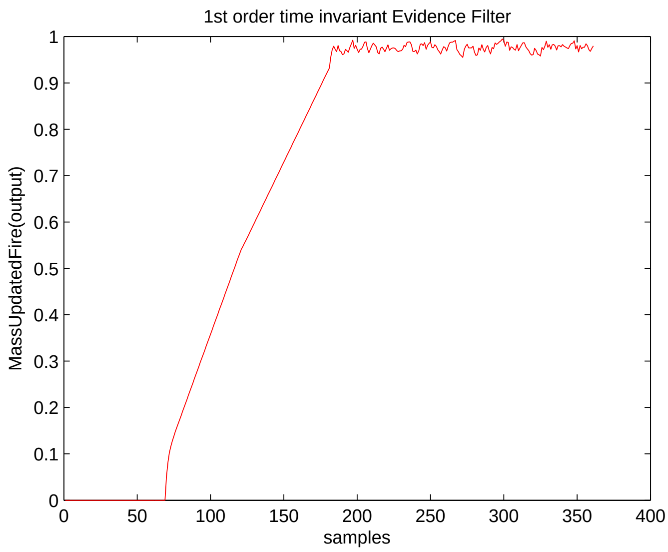


Fig. 3.4: First order Evidence Filter output

Therefore we first construct the input evidence signal as described in the previous section and pass through the Evidence Filter. The results are shown in Figure 3.5. When the pole moves towards the unit circle, system becomes more sluggish (high rise time) but absorbs less noise (sudden artifacts due to transmission drops) to the system and vise versa. However the rise time and the robustness to artifacts should be compromised to obtain the desired results. Therefore in the next section we propose a linear time varying (LTV) Evidence Filter to achieve above objective.

3.4 Artifact Modelling in Linear Time Varying Evidence Filtering

We name this approach as an ***Event Triggered Time Varying Evidence Filter***. The proposed filter detects the noise signature (sudden artifact) and change the pole value accordingly.

if *absolute(mass(Fire)(t)-mass(Fire)(t-1))*$\geq$*Threshold* **then**
  assign a high pole value ;
else
  assign a low pole value
end

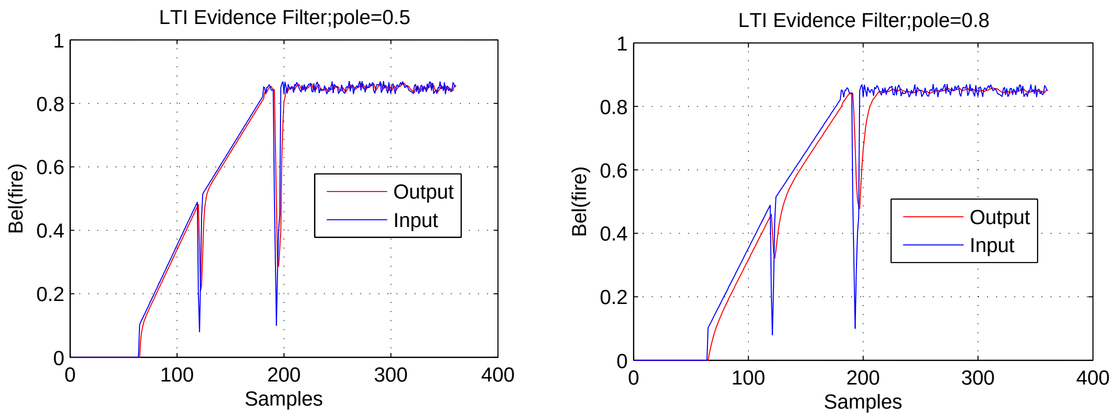


Fig. 3.5: Output from first order Evidence filter a) alpha=0.5, beta=0.5 b) alpha=0.8, beta=0.2

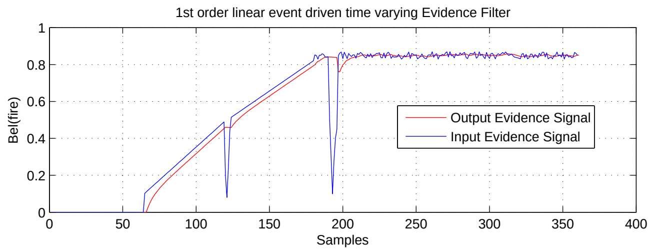


Fig. 3.6: Adaptive filter output, time varying coefficients

3.4.1 Results Analysis

Figure 3.6 shows the output evidence signal from the Event Triggered Evidence Filter. System is sluggish to noise while updates itself quickly with the incoming evidences. Even though the input signal varies rapidly (from 180-360) output signal is very smooth compared to the input evidence signal (Figure 3.8).

When we compare the output signals in both LTI and LTV Evidence Filters, better results can be obtained from the LTV filter. It is robust to sudden artifacts and produces a signal with a low rise time.

In the LTV case, the filter will be even more sluggish if the fire declined suddenly. However based on the literature review, we assume fire decline gradually. The filter will not be sluggish in that situations as the filter has the ability to differentiate artifacts with decline of the fire. Figure 3.9 illustrates the filter behaviour at the fire declining stage.

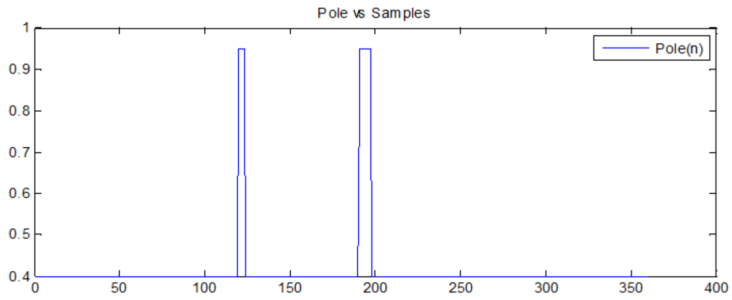


Fig. 3.7: Pole changes from .45 to 0.9

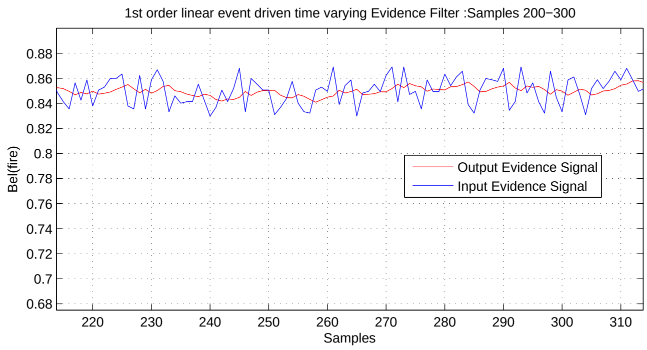


Fig. 3.8: Enlarged input vs output evidence signals

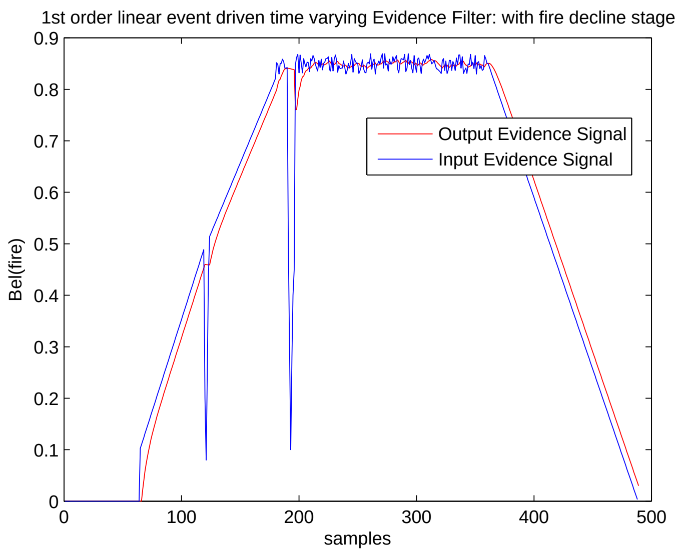


Fig. 3.9: 1st order event triggered time varying Evidence Filter with fire declined stage

Chapter 4

Fire Scenario Development

As discussed in previous sections, one of our primary objectives is to address emergency response management in a Wireless Sensor Network. Emergencies can be gas leakages, fire, earthquakes etc. In order to verify our frameworks and algorithms we consider fire propagation in an indoor environment.

Therefore we simulate real fire propagation scenarios using a fire simulator developed by NIST, United States [1]. The study reported in this chapter is based on the NIST research on residential fire propagation.

According to the NIST, the location of fire origin at the building, ignition source and the first item ignited are the important characteristics of developing the fire scenarios. Furthermore the data can be obtained for most frequent fires, and fires resulting in the greatest number of deaths.

- fire location (living room, bedroom, kitchen, and other)
- fire type (smoldering, flaming, and fast flaming)
- first item ignited.

The five main fire scenario models developed in NIST are shown below,

- smoldering upholstered furniture in the living room,
- flaming upholstered furniture in the living room,
- smoldering mattress in the bedroom,
- flaming mattress in the bedroom, and
- cooking materials in the kitchen.

Residential fires are categorized into flaming (having flames and generating massive heat) and smoldering (having less flames and heat and more smoke) fires. Additionally, some actions such as toasting a bread or lighting a cigarette, typical cooking activities, smoking or candle flames may generate nuisances that can be mistaken for real fire [33].

4.1 FDS (Fire Dynamic Simulator)

FDS is used as the fire simulator for scenario generation and sensor data collection in this thesis. We consider a sensor network which is deployed on the ceiling, and the sensor data (temperature, optical density, smoke) generated over a given time period is recorded. Temporal and spatial distribution of the sensor data is analyzed.

Figure 4.1 shows a fire propagation in a living room. The ignition point is at a couch.

The temperature, smoke and optical density variations during the fire at two different sensor nodes are shown in Figures 4.2-4.4. Figure 4.5 illustrates the normalized values for three types of sensor modalities.

Scenario 1: Smoldering fire in a living room In the living room door is open, no fan. One couch seat cushions, two couch armrest, one couch back cushions. Ignition source is on couch.

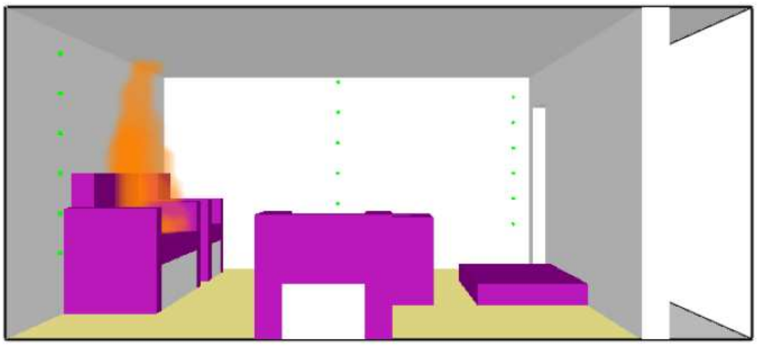


Fig. 4.1: Simulated room fire in FDS

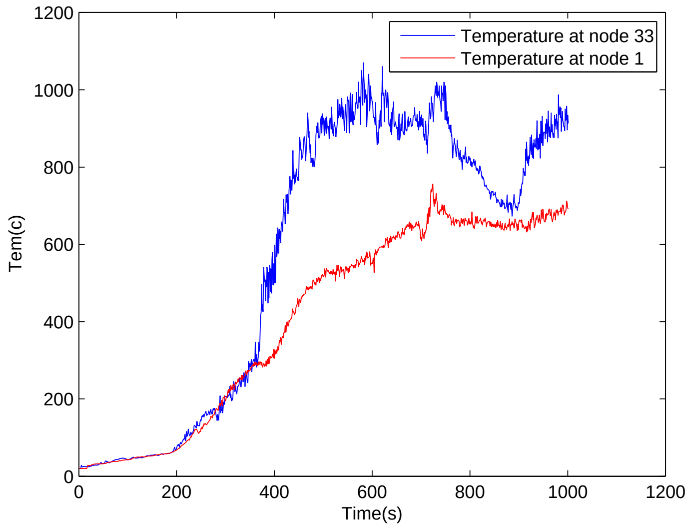


Fig. 4.2: Comparison of temperature between node 1 and node 33, node 1 is away from the fire ignition point and the node 33 is just on top of the fire ignition point

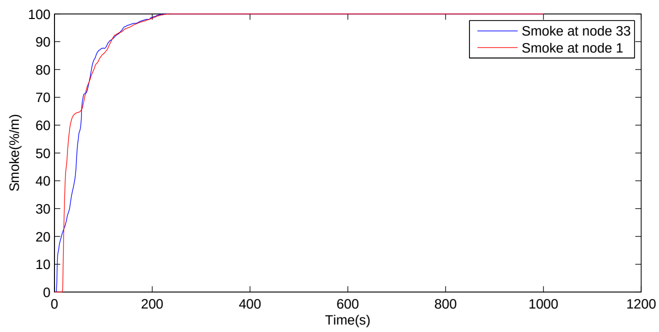


Fig. 4.3: Comparison of smoke level between node 1 and node 33, node 1 is away from the fire ignition point and the node 33 is just on top of the fire ignition point

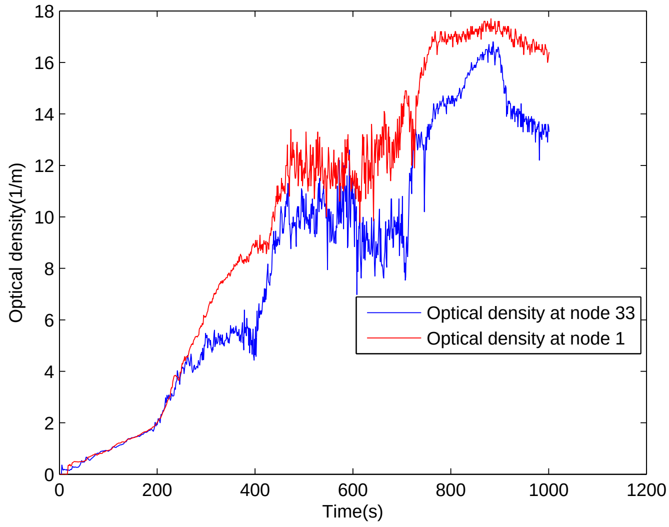


Fig. 4.4: Comparison of optical density between node 1 and node 33, node 1 is away from the fire ignition point and the node 33 is just on top of the fire ignition point

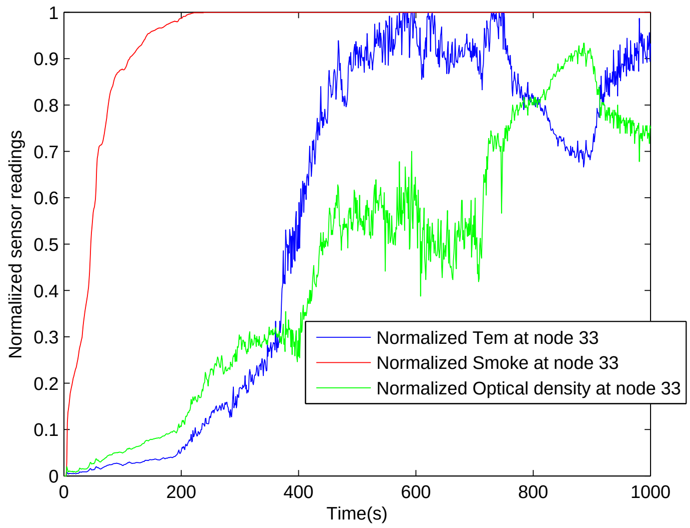


Fig. 4.5: Normalized sensor readings at node 33 for temperature, smoke and optical density

Chapter 5

Dempster-Shafer Information Filtering

The Dempster-Shafer (DS) Information Filtering framework is introduced in this section. Multiple Input Single Output and Single Input Single Output linear time invariant filtering techniques for information fusion in WSNs are introduced and described. The work reported in [34] uses the DS Information Filtering framework (Temporal Evidence Filter) for self-organization of sensor nodes based on the severity of an emergency. In this section we analyse and verify temporal Evidence Filter comparing the results with Dempster-Shafer evidence combination technique. Furthermore we introduce higher order Spatio-Temporal Evidence Filtering technique to make a sensor node possess more knowledge on the scenario.

State of the environment under observation is defined as x_i, time instances as t_i, space coordinates as θ_i, and modalities as s_i. Dempster-Shafer Frame of Discernment (FOD) is defined over states under observation as,
$DS\ FOD$=$\{x_1, ...x_n\}$.

5.1 Temporal Evidence Filtering

5.1.1 Single Input Single Output Evidence Filter

Input evidence signal to SISO Evidence Filter is modeled using two methods, the weighted averaging method fuse multi modality sensor data at the normalized measurement level and the final normalized weighted average function is then used to obtain relevant DS mass functions. The second method obtains evidences from each modality and fuses using any DS evidence combination method. [8].

1. Weighted averaging method: Normalized weighted average function is obtained ($X_{average_{t_k}}$) as follows,

$$X_{average_{t_k}} = \sum_{i=1}^{N} \alpha_{i,k} X_{s_i,t_k} \tag{5.1}$$

N is the number of sensor modalities, X_{s_i,t_k} is the normalized sensor measurement at i^{th} sensor modality at k^{th} time instance. Where for a fixed k, constant $\alpha_{i,k} \geq 0$ and $\sum_{i=1}^{N} \alpha_{i,k} = 1$; to ensure that the normalized values span over 0 to 1.

The normalized weighted average is used to obtain DS mass functions at each time instance t_k.

2. Dempster-Shafer Evidence Combination:

$$\zeta_{s_i,t_k} = g(X_{s_i,t_k}) \tag{5.2}$$

Where function g can be a simple threshold based function or any function defined according to the application and the situation under observation. ζ is the derived evidence. This can be belief or plausibility.

$$\lambda_{t_k} = f(\zeta_{s_i,t_k}) \tag{5.3}$$

Where function f can be any evidence combination method, several popular methods to combine evidences are presented in [35] to overcome the certain drawbacks associated in initial DS evidence combination rule. λ denotes the fused evidence.

Finally, the fused input evidence signal is obtained for the event of interest B as follows, by ordering the fused evidence λ over time.

$I(t) = Bel(B)(t)$ or $I(t) = Pl(B)(t)$

$I(t)$ is the input evidence signal. Bel and Pl derives from DS theory and refer to belief and plausibility functions. B is a hypothesis consisting of one or more states x_i.

A general higher order Evidence Filter can be considered as a higher order SISO filter.

$$Bel(B)(t) = \sum_{i=1}^{N} \alpha_i Bel(B)(t - i) + \sum_{i=1}^{N} \beta_i Bel(B|A)(t-i) \quad (5.4)$$

$\alpha_i, \beta_i \geq 0$ and $\sum_{i=1}^{N} \alpha_i + \sum_{i=1}^{N} \beta_i = 1$.

The conditions above for α and β are to ensure the belief and plausibility functions constitute valid DS functions.

Figure 5.1 represents the SISO Evidence Filter for belief functions. A similar diagram can be used to illustrate the plausibility function (for simplicity we neglect the input evidence signal at $T = 0$).

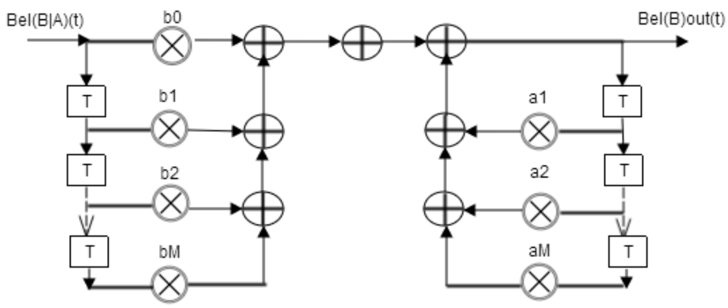


Fig. 5.1: Single Input Single Output Evidence Filter

5.1.2 Multiple Input Single Output Evidence Filter

In the MISO Evidence Filter each sensor-modality generates a separate input evidence signal by obtaining evidences according to 5.2. This facilitates one to directly fuse multi-modality sensor data over time.

$$Bel(B)(t) = \sum_{i=1}^{M} \alpha_i Bel(B)(t - i) + \sum_{k=1,i=0}^{N,M} \beta_{s_k,i} Bel_{s_k,i}(B|A)(t - i) \quad (5.5)$$

$$Pl(B)(t) = \sum_{i=1}^{M} \alpha_i Pl(B)(t - i) + \sum_{k=1,i=0}^{N,M} \beta_{s_k,i} Pl_{s_k,i}(B|A)(t - i) \quad (5.6)$$

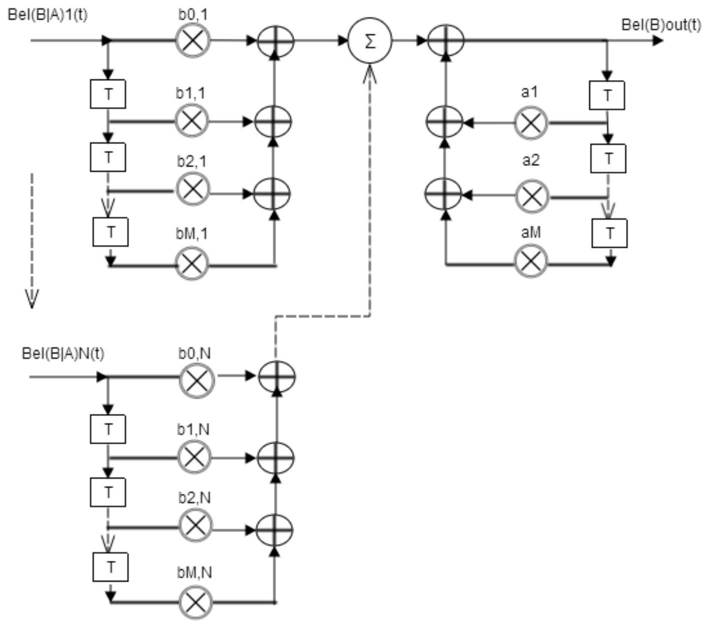


Fig. 5.2: Multiple Input Single Output Evidence Filter

$$\alpha_i \geq 0; \beta_{s_k,i} \geq 0 \tag{5.7}$$

$$\sum_{i=1}^{M} \alpha_i + \sum_{k=1,i=0}^{N,M} \beta_{s_k,i} = 1; \tag{5.8}$$

The conditions in 5.7 and 5.8 are to ensure that the belief and plausibility functions constitute valid DS functions.

Figure 5.2 represents the MISO Evidence Filter for belief functions. A similar diagram can be used to illustrate the plausibility function.

During the information filtering, the filter updates the existing knowledge base with the new evidence while taking into account the inertia and integrity of its already available knowledge. Coefficient α is the weight given to the available knowledge while β is the weight given to incoming evidence.

5.2 Spatio-Temporal Evidence Filter

The temporal Evidence Filter enables each node to possess only partial knowledge on the environment under observation. However to process information more accurately and effectively each node should have some global knowledge on the environment. This can be achieved by extending the temporal evidence filter to spatio-temporal evidence filter.

More power is required for data transmission compared to computation in sensor networks. Distributed information processing in sensor networks requires less power due to the above reason. Not all the data gathered at each node is sent to the central processing node, instead the results computed by each node are sent to the central node. In this way the power required for the transmission can be saved.

In the proposed framework, a Spatio-Temporal Evidence Filter runs on each sensor node and the decision making algorithm is handled by the central node. A three dimensional system is analyzed, 2D (x, y) in space and time (t). Two types of multidimensional methods can be used to obtain the state at each node.

- Three dimensional difference equation

$$\begin{aligned} Bel(B)(x,y,t) = \sum_{i=1}\sum_{j=1}\sum_{k=1}\alpha_{i,j,k}Bel(B)(x-i,y-j,t-k)+ \\ \sum_{a=1}\sum_{b=1}\sum_{c=1}\beta_{a,b,c}Bel(B|A)(x-a,y-b,t-c) \end{aligned} \tag{5.9}$$

- State space models : Fornasini-Marchesini (FM) [36] and Givone-Roesser [37] State Space Models
  FM model

$$\begin{aligned} X(x,y,t) &= A_{011}X(x,y-1,t-1) + A_{101}X(x-1,y,t-1) \\ &+ A_{111}X(x-1,y-1,t-1) + B_{010}U(x,y-1,t) + B_{100}U(x-1,y,t) \end{aligned} \tag{5.10}$$

$$Y(x,y,t) = CX(x,y,t) + DU(x,y,t) \tag{5.11}$$

  where X is the state vector, U is the input vector and Y is the output vector of the system. All the vectors are three dimensional (2-D in space and time). The matrices A, B, C are real matrices of appropriate dimensions [37].

5.3 Spatio-Temporal Evidence Filtering With Belief Vectors

The Spatio-Temporal and Temporal Evidence Filtering frameworks produce Dempster-Shafer belief values with magnitudes. However during our research we encountered the necessity of having an Evidence Filter which produces DS belief values with both magnitude and direction. The DS belief vectors can be effectively used in navigation and predictions. For example during an emergency, the output of the Evidence Filter indicates the severity level and the probable direction of the emergency (i.e. fire) propagation. Therefore the objective of this part of the research is to develop a DS Belief Vector (i.e. severity vector).

The output of the Spatio-Temporal Evidence Filter (introduced in the previous section) depends on the past knowledge base of the node, the inputs and the past knowledge base of its neighbouring nodes. We follow the same approach and extend it to estimate the DS belief vector.

A four dimensional system is analyzed, 2D in space, time and direction. As in the previous section, Multidimensional difference equations are used to obtain the state at each node.

$$\begin{aligned} Bel(B)(x,y,t,\theta) = &\sum_{i=1}\sum_{j=1}\sum_{k=1}\sum_{l=1}\alpha_{i,j,k,l}Bel(B)(x-i,y-j,t-k,\theta-l)+ \\ &\sum_{a=1}\sum_{b=1}\sum_{c=1}\sum_{d=1}\beta_{a,b,c,d}Bel(B|A)(x-a,y-b,t-c,\theta-d) \end{aligned} \quad (5.12)$$

If the gradient of the DS belief values denoted by m_{x_i,y_i}.

$$m_{x_i,y_j} = \frac{\partial}{\partial t}(Bel(B|A)(x_i,y_j,t,\theta)) \quad (5.13)$$

θ can be determined from the m_{x_i,y_j} of all the neighbours.

$$\theta = \psi(m_{x_i,y_j}, Bel(B|A)(x_i,y_j,t,\theta)) \quad (5.14)$$

$\forall x_i, y_j$ are locations of neighbouring nodes

5.4 Experimental Scenario for Fire Spread Model

Wireless sensor networks (WSNs) offer opportunities to minimize the impact caused by emergencies. Emergencies range from fire, gas leakages, earthquakes to terrorist attacks. Fire detection and prediction plays an important role in indoor emergencies and disaster management due to the high number of deaths reported all over the world frequently. The results gathered from WSNs are highly useful for firefighters during their rescue operations. To obtain an accurate situational assessment on the environment under observation, the WSNs often use multiple sensor modalities, and the measurements are gathered from several locations and perhaps from different orientations. Moreover, during an emergency high ground noise is present with node and link failures compared to non-emergency situations.

Furthermore various types of fire models can be found such as smoldering fire, flaming fire, nuisances. Therefore there are several uncertainties involved in the fusion of data obtained from such situations. Many WSNs use inexpensive sensors to reach a tradeoff between cost and performance. Hence sensor measurements may be inaccurate, and the results derived will be unreliable. This has a direct impact on the safety of both the rescuers and victims.

5.4.1 Simulation Setup: Temporal Evidence Filtering

A Fire scenario is developed using Fire Dynamic Simulator (FDS) developed by National Institute of Standard and Technology (NIST), United States [38].

A living room consists with one couch seat cushion, two couch armrests and one couch back cushion. There is no fan. The door is open, so that the fire can easily propagate outside of the living room. The fire scenario we generate here is of smoldering type. It initially generates less flame and heat with more smoke. A grid based sensor network is deployed at the ceiling consists with 36 (9x4) sensor nodes. Each sensor node is equipped with three sensors, to sense temperature, smoke, and optical density. At $t = 0$, ignition starts. The ignition source is on the couch. Figure 5.3 shows the simulation setup in FDS smoke view. Sampling time is set to 1s.

The objective of this setup is to detect emergencies, and determine the growth stage of the fire or the severity level. Therefore the DS Frame of Discernment (FOD) is defined as,

$DS\ FOD(\Theta)$=$\{no\ emergency,\ low_1, low_2.., low_n, medium_1, medium_2, ..$

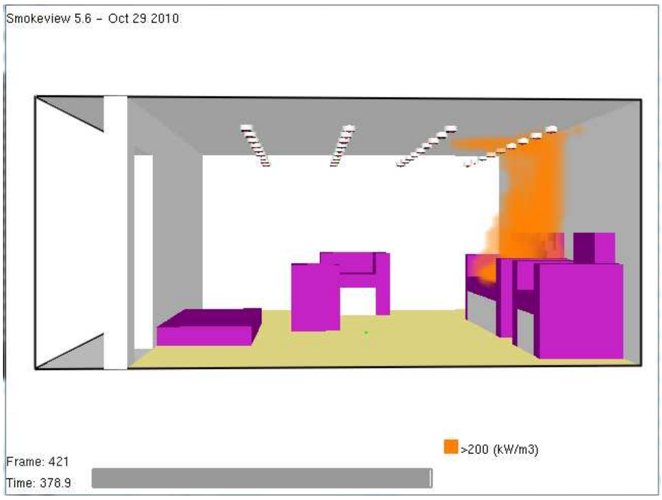


Fig. 5.3: Simulation setup: Living room, Sensor nodes are deployed at the ceiling

$medium_m, high\}$
If $m = n = 1$, number of hypothesis is $2^4 = 16$.
At each time instant, each sensor node takes measurements for temperature, smoke, optical density and assigns masses to respective DS hypothesis. Zero mean white Gaussian noise is added to raw sensor measurements of temperature, smoke and optical density.

5.4.2 Mass Assignment and Construction of the Evidence Table

Normalized sensor measurements are obtained at each time instant for each sensor modality. The mapping from normalized values to related masses can be obtained by suitable modality functions. Here we use threshold based mapping. For fire detection, the hypothesis interested (B) is (low, medium, high). Belief or plausibility functions are obtained according to DS theory. The evidence table (5.1) is constructed to generate input evidence signals. In the Evidence Table abbreviations given below are used.
m_n= Mass assigned to 'no emergency'
m_l= Mass assigned to 'low'severity
m_m= Mass assigned to 'medium'severity
m_h= Mass assigned to 'high'severity
$m_{n,l}$= Mass assigned to 'no emergency or low'
$m_{l,m}$= Mass assigned to 'low or medium'

Table 5.1: Evidence Table for Severity of Fire

Proposition(B)	Mass(B)	Belief(B)	Plausibility(B)
No emergency	m_n	m_n	$m_n + m_{n,l}$
Low	m_l	m_l	$m_l + m_{n,l} + m_{l,m} + m_{l,m,h}$
Medium	m_m	m_m	$m_m + m_{l,m} + m_{m,h} + m_{l,m,h}$
High	m_h	m_h	$m_h + m_{m,h} + m_{l,m,h}$
No emergency, Low	$m_{n,l}$	$m_n + m_l + m_{n,l}$	$m_n + m_l + m_{n,l} + m_{l,m} + m_{l,m,h}$
Low, Medium	$m_{l,m}$	$m_l + m_m + m_{l,m}$	$m_{n,l} + m_l + m_m + m_{l,m} + m_{m,h} + m_{l,m,h}$
Medium, High	$m_{m,h}$	$m_m + m_h + m_{m,h}$	$m_m + m_h + m_{m,h} + m_{l,m,h}$
Low, Medium, High	$m_{l,m,h}$	$m_l + m_m + m_h + m_{l,m}+$ $m_{m,h} + m_{l,m,h}$	$m_l + m_m + m_h + m_{l,m}+$ $m_{m,h} + m_{l,m,h} + m_{n,l}$

Table 5.2: Results comparison

Fusion Method	Mean Error	Error Variance
MISO Evidence Filter	2.48%	0.66%
SISO Evidence Filter	3.88%	0.82%
Dempster-Shafer Evidence Combination	13.46%	9.01%

$m_{m,h}$= Mass assigned to 'medium or high'

$m_{l,m,h}$= Mass assigned to 'low or medium or high'

Out of 2^4 hypothesis, we included only 8 hypothesis in the table assuming all the other hypothesis are assigned 0.

5.4.3 Sensor Fusion

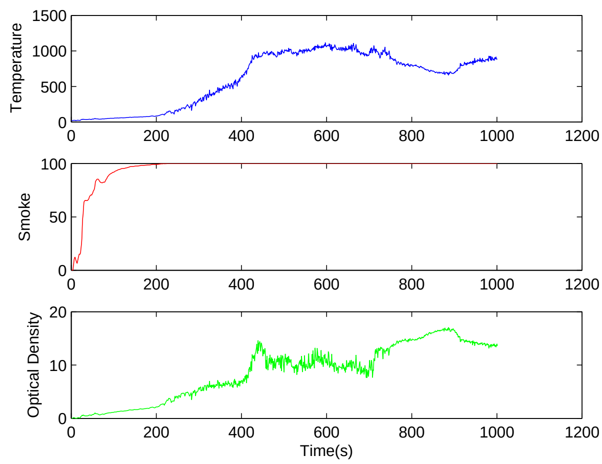


Fig. 5.4: Sensor measurements at node 32 before noise is added

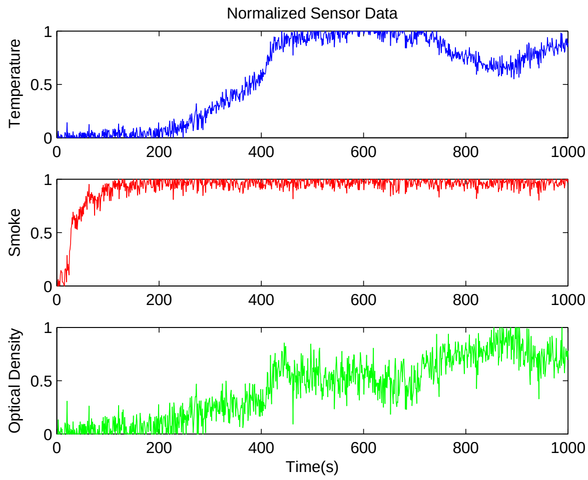


Fig. 5.5: Normalized sensor measurements at node 32 before noise is added

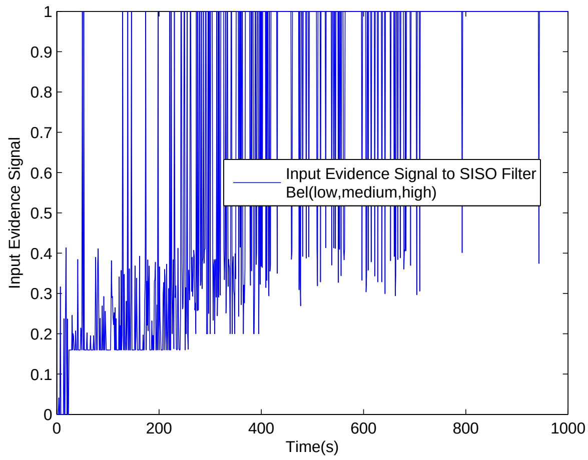


Fig. 5.6: Input evidence signal of SISO Filter-fused multi-modality evidences at node 32

SISO Evidence Filter

Gathered evidences for multiple modalities are fused using DS evidence updating method. The fused evidences are temporally ordered and passed through first order SISO LTI Filter.

$$Bel(B)(t) = \alpha_t Bel(B)(t-1) + \beta_t Bel(B|A)(t) \tag{5.15}$$

$$Pl(B)(t) = \alpha_t Pl(B)(t-1) + \beta_t Pl(B|A)(t) \tag{5.16}$$

A narrow information bandwidth is taken, by assigning a high value to α_t. Lets take α_t= 0.9, and β_t= 0.1.

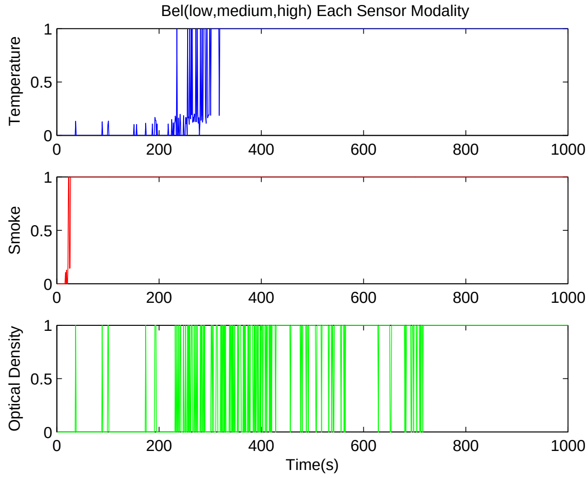


Fig. 5.7: Input evidence signals of MISO Filter at node 32

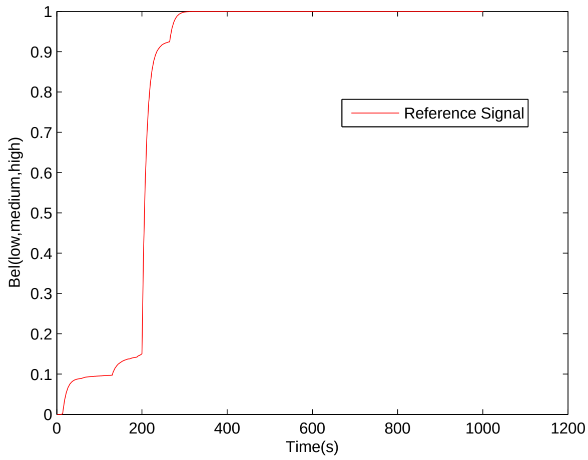


Fig. 5.8: Reference fire signal

MISO Evidence Filter

Gathered evidences for multiple modalities are separately ordered over time and separate input evidence signals are generated. Multiple signals are passed through first order MISO LTI Filter.

$$Bel(B)(t) = \alpha_t Bel(B)(t-1) + \sum_{i=1}^{n} \beta_{t,s_i} Bel_{s_i}(B|A)(t) \tag{5.17}$$

$$Pl(B)(t) = \alpha_t Pl(B)(t-1) + \sum_{i=1}^{n} \beta_{t,s_i} Pl_{s_i}(B|A)(t) \tag{5.18}$$

A narrow information bandwidth is taken, by assigning a high value to α_t.

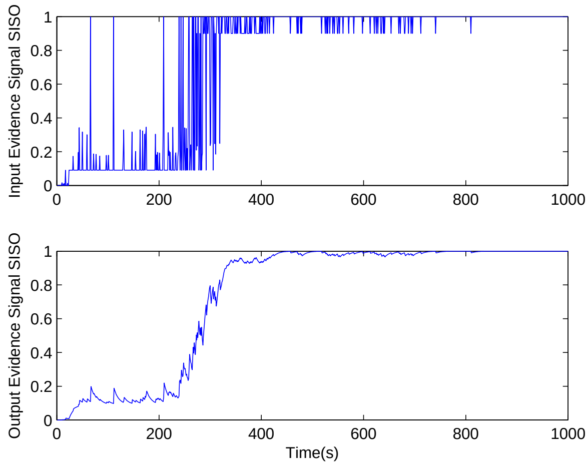


Fig. 5.9: Input vs output evidence signals of SISO filter at node 32

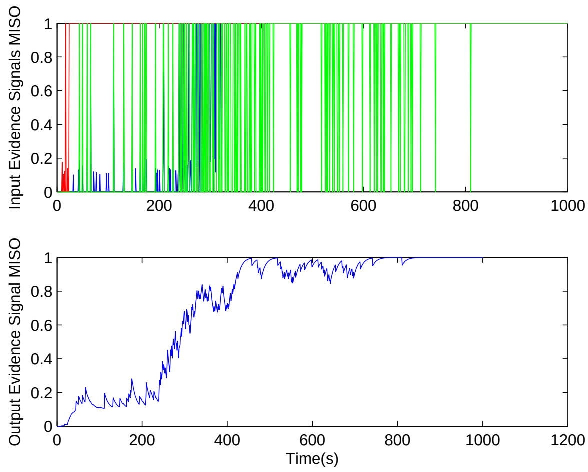


Fig. 5.10: Input vs output evidence signals of MISO filter at node 32

Lets take α_t= 0.9, and β_{t,s_1}= β_{t,s_2}= β_{t,s_3}= $\frac{1-\alpha_t}{3}$. In both cases A is taken as the *DS FOD* (Θ).

5.4.4 Results Analysis of Temporal Evidence Filtering

Fig. 5.5 shows the normalized sensor readings of temperature, smoke and optical density before noise is added. Within the proposed framework, DS-Evidence Combination input signal modeling under SISO Evidence Filter, MISO Evidence Filter are implemented. Input evidence signal to SISO Evidence Filter is shown in Fig. 5.6. This clearly illustrates the high ambiguity in the fused results during the fire growth from low to high level.

Three input evidence signals of the MISO Evidence Filter are shown in Fig.

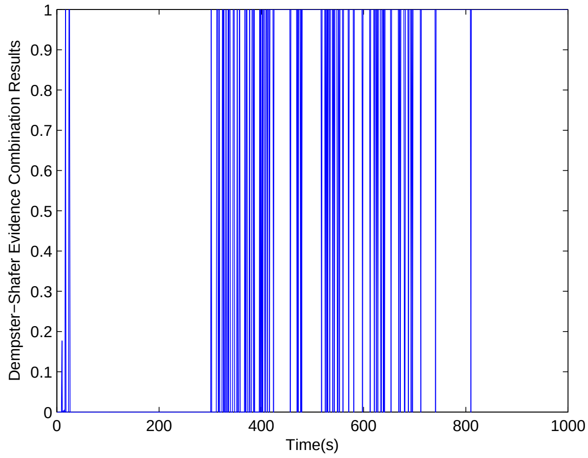


Fig. 5.11: Output of DS evidence combination over time at node 32

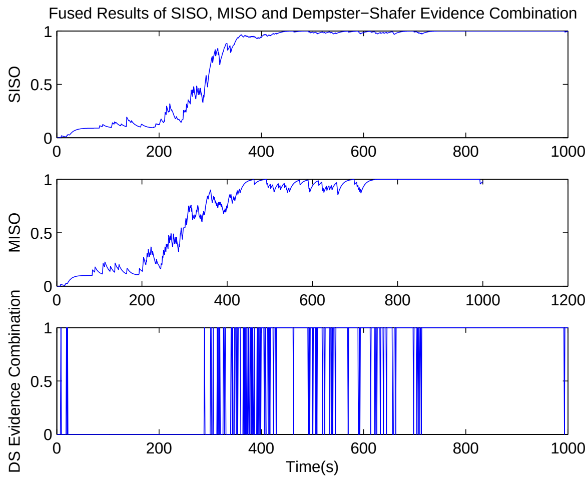


Fig. 5.12: DS combination and SISO evidence filter outputs at node 32

5.7. These input signals are not fused until those have been sent to the filter. Ambiguity and uncertainty in the input signals are very high compared to the output evidence signal which is shown in the Fig. 5.10.

Basically in both cases fusing over time has provided more reasonable indication of the fire scenario with less ambiguity for dynamically varying states when the noise is present. Fig. 5.9 and Fig. 5.10 compare input and output evidence signals of both filters. Fig. 5.11 shows the results obtained from DS evidence combination rule. The outputs from all three sensor fusion methods (SISO, MISO and DS evidence combination) are shown in Fig. 5.12. The error variation with respect to time in SISO, MISO Evidence Filters and DS combination are shown in Fig. 5.13. Mean errors/ error variances for DS combination and Evidence

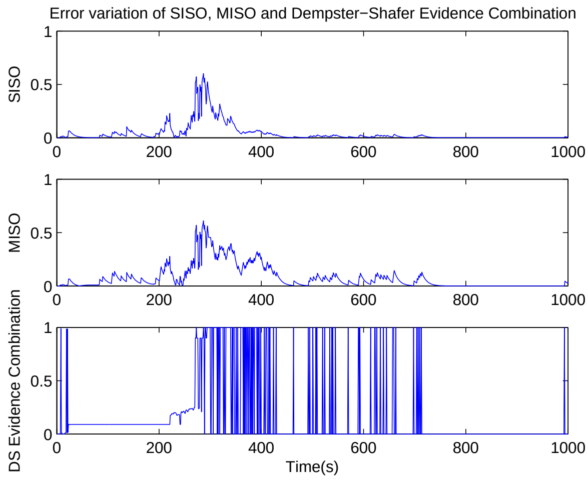


Fig. 5.13: Error variation of DS combination and SISO evidence filter output at node 32

Filter are shown in Table 5.2. According to the results obtained, the proposed methods clearly outperforms the DS evidence combination.

At the beginning of the fire we can observe a sudden increment in the output signal, next there is a sluggishness due to ambiguity in temperature and optical density. However after sometime when the temperature and optical density measurements start giving the information on fire, the filter quickly catches up and gives expected information of the fire.

In both cases we considered a narrow information bandwidth, by assigning large weights to the past knowledge base to make the system absorbs less noise. However this makes the system to be more sluggish to the incoming evidences. Compromising these two aspects can be achieved by introducing a time varying filter.

Note that all the plots shown in the simulation are taken for the 32^{nd} sensor node which is just above the ignition point. We have obtained the results for other sensor nodes (1-36) as well. Each application which runs on the proposed framework can develop its own algorithm to manipulate the spatial correlation of the output evidence signals of each node. In this manner, distributed DS Information Filtering is performed at each child node and base station node separately according to the algorithms specific to the application.

5.4.5 Spatio-Temporal Filtering to Estimate the Fire Severity

The algorithm developed in this section focuses on estimating the severity state of the fire/gas distribution in a building using a grid sensor network.

The same algorithm runs on all the nodes and the decision making algorithm runs in the central node. Once an emergency occurs, the emergency reporting node immediately sends a message to the central node. Then the central node broadcasts a message to all the nodes indicating the fire ignition point. After receiving the emergency message, each node starts running the algorithm (reducing the sampling time). Computed states are then sent to the central node to make a decision, else the actuation tasks can be done by the sensor nodes.

Assumptions

1. Sensor network is modeled as a grid network
2. One sampling time delay is considered
3. Fire/gas propagation approximately follows a constant speed and a circular spreading shape
4. No noise or node, link failures are considered

Following difference equation is considered for Spatio-Temporal Evidence Filter

$$
\begin{aligned}
X(x,y,t) &= A_{011}X(x,y-1,t-1)+A_{101}X(x-1,y,t-1)+A_{111}X(x-1,y-1,t-1) \\
&+B_{011}U(x,y-1,t-1)+B_{101}U(x-1,y,t-1)+B_{111}U(x-1,y-1,t-1)+B_{000}U(x,y,t) \\
Y(x,y,t) &= CX(x,y,t) \qquad (5.19)
\end{aligned}
$$

Note: All the states are in Dempster-Shafer belief values
$Bel(B)$; $B=$ state of the fire in terms of severity (low, medium, high).

When each node estimates its current state by considering the previous states of its neighboring nodes, the node should have a basic knowledge regarding the fire propagation to estimate the correct coefficient values. The algorithm proposed here chooses the best neighbors to give high coefficients. All the other states of the neighboring nodes are assigned low coefficient values. (or simply the data sent from other neighbors can be ignored).

High Level Methodology: Spatio-Temporal Evidence Filter

The network is dynamically and virtually divided in to 9 regions.

Once the network is triggered according to the location of the fire initiating node, each sensor node determines its region. $(A, B, C, D, E, F, G, H, O)$. Based on the regions of its peer nodes, the filter coefficients are determined by each node. Then the node calculates its current state and the output and sends the output state to its neighboring nodes. The high level methodology can be described as below,

1. Temporal-Evidence Filter (SISO or MISO) runs in each node.
2. A sensor node reports about the fire to the central node
3. Central node triggers the whole network, (Message: fire/gas etc. and reporting node number)
4. Switch to the Spatio-Temporal Evidence Filter (section 5.2)
5. Each node determines the coefficients based on the region.
6. Each node calculates its current state using any method (FM/GR/m-D difference equation)
7. Each node sends the output value to its neighbouring node and to the central node.
8. Central node can plot the belief maps and build up the knowledge about the environment and filter out the information based on the results further
9. Central node can estimate the speed of the fire/gas propagation by detecting the propagation of higher belief values in space and time.
10. Estimated values can be further refined with the time (performing many iterations).

Algorithms: Spatio-Temporal Evidence Filter

All the nodes run the same distributed algorithm to estimate the severity.

```
Data: Once the output of the Temporal Evidence Filter exceeds the given
      threshold any node can report it to the central node
if Emergency message is received from the central node then
|   Calculate its region ;
|   if Sampling timer fired then
|   |   Sample all sensor signals ;
|   |   Combine them to generate input 'U' ;
|   |   Perform local state space computation. Based on the region the
|   |   state space equation gets changed or the coefficient values are
|   |   determined. ;
|   |   Transmit state X(x,y,t) to the neighbouring nodes
|   |   if Output Y(x,y, t) greater than the threshold then
|   |   |   Execute local actuation tasks if needed, based on the
|   |   |   application ;
|   |   |   Send event indication message to the base node Node goes to
|   |   |   sleep ;
|   |   else
|   |   |   do nothing
|   |   end
|   else
|   |   Node is in sleep state
|   end
else
|   Not an emergency
end
```

Algorithm 1: Distributed Spatio-Temporal Algorithm

```
if Emergency message is received from the fire ignition node then
|   Broadcasts the message to all the nodes indicating the reporting node
|   number ;
|   Receive the calculated output states of the each node ;
|   Generate DS-belief maps;
else
|   Not an emergency
end
```

Algorithm 2: Algorithm runs in the central node to indicate the severity of the fire

5.4.6 Simulation Setup: Spatio-Temporal Evidence Filter

A grid sensor network with 100 nodes, 10 x 10 in size is considered. The distance between each two nodes is considered to be same and 1 m. Figure 5.14 shows the grid sensor network and the virtual nine regions created based on the fire ignition location. All the nodes are numbered from 1 to 100. Speed of the fire is constant. The fire ignition can happen randomly at any point.

Following Figures 5.15-5.22 are taken for 1 ms speed of (fire) propagation, sampling time is 1s, fire ignition node is '35'. Belief maps are generated at the central node according to the output belief values received from each sensor node.

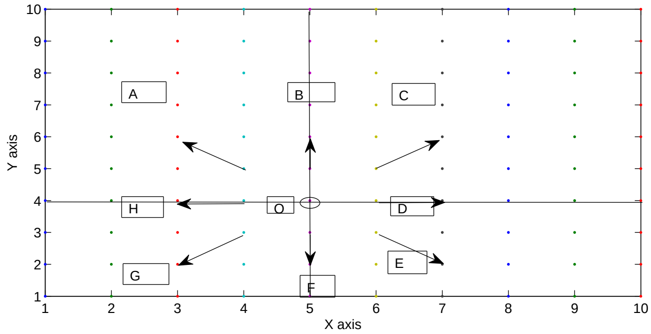


Fig. 5.14: Grid sensor network. Fire starts at node 35;(5,4). Regions are shown in boxes.

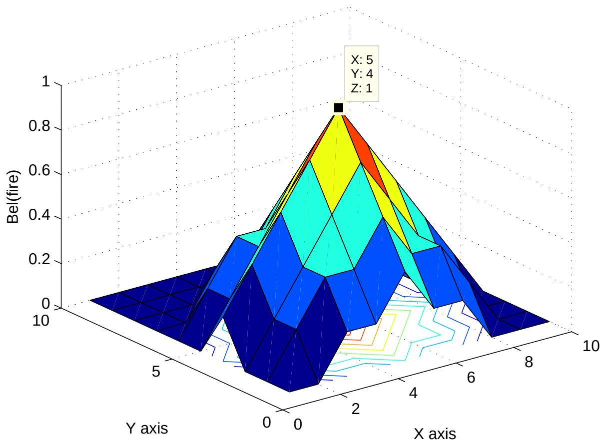


Fig. 5.15: Output states of the each node in the network, at time t=1s

The belief pattern identification algorithm runs in the central node while creating the belief maps at each sampling time.

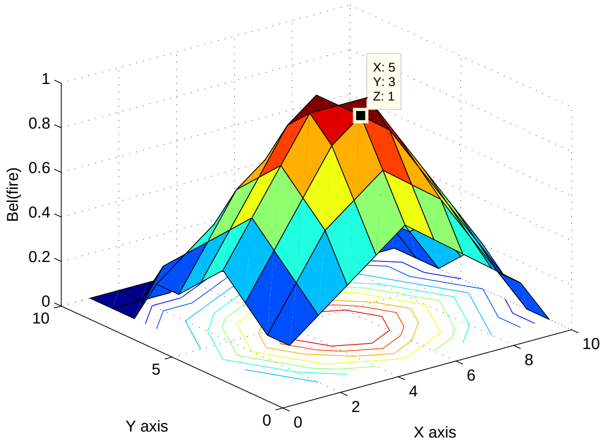


Fig. 5.16: Output states of the each node in the network, at time t=2s

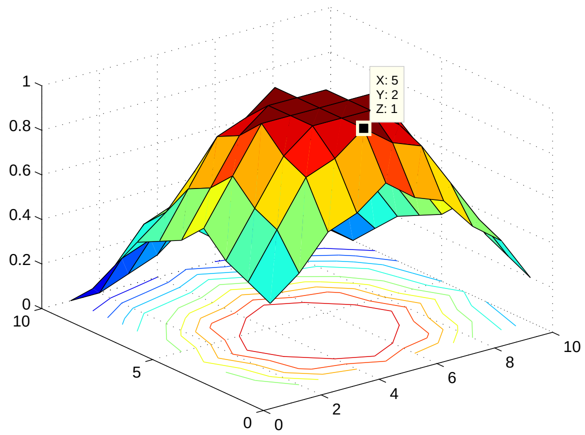


Fig. 5.17: Output states of the each node in the network, at time t=3s

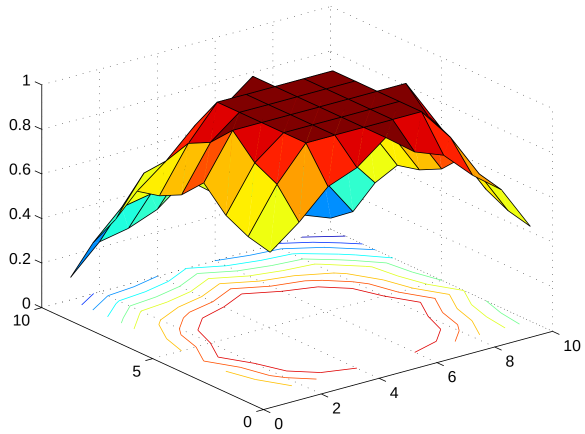


Fig. 5.18: Output states of the each node in the network, at time t=4s

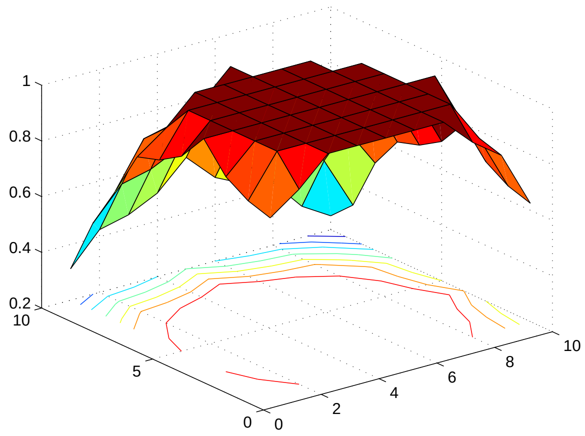


Fig. 5.19: Output states of the each node in the network, at time t=5s

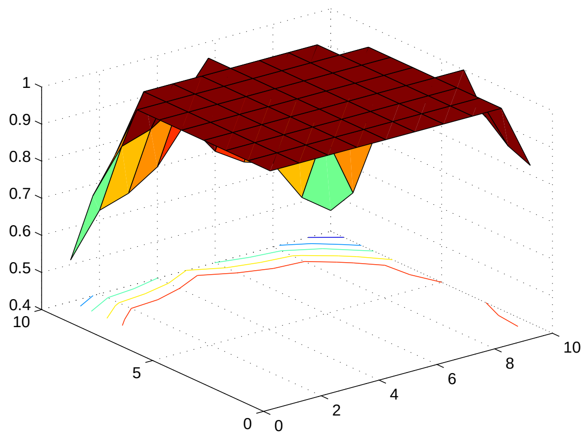


Fig. 5.20: Output states of the each node in the network, at time t=6s

5.4.7 Spatio-Temporal Evidence Filter-Severity Vector Generation

The algorithm developed in this section is an extension of the Spatio-Temporal Filter which was simulated in the previous section. This mainly aims to estimate the severity state in terms of magnitude and the direction of the fire/gas distribution in a building using a grid sensor network.

The distributed algorithm runs on all the nodes and the decision making algorithm runs in the central node. Once an emergency occurs, the emergency reporting node immediately sends a message to the central node. Then the central node broadcasts a message to all the nodes indicating the fire ignition point.

After receiving the emergency message, each node starts running the Spatio-

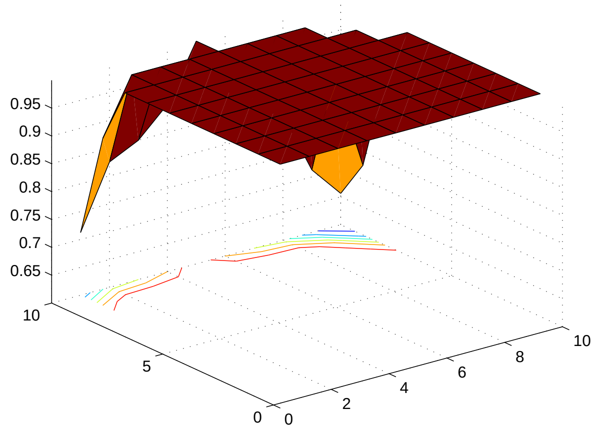


Fig. 5.21: Output states of the each node in the network, at time t=7s

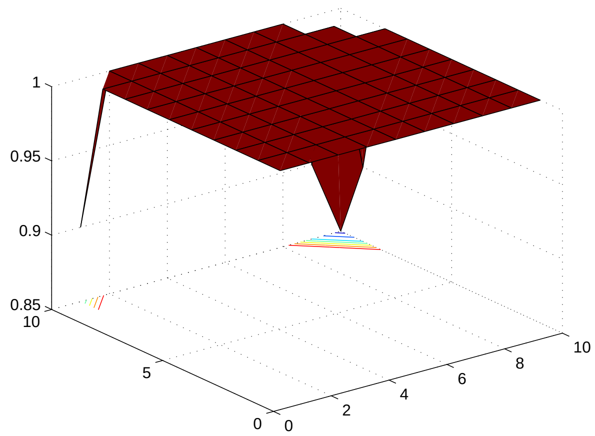


Fig. 5.22: Output states of the each node in the network, at time t=8s

Temporal Belief Generation algorithm (reducing the sampling time). Computed states are then sent to the central node to make necessary decisions, else the actuation tasks can be done by the sensor nodes.

Assumptions

1. Sensor network is modeled as a grid network
2. No delay is considered for the communication between neighbouring nodes
3. Fire/gas propagation approximately follows a constant speed and a circular spreading shape
4. No noise or node, link failures are considered

Each sensor node communicates with the neighbours who are in one hop communication range. Therefore in the grid sensor network each node has maximum eight neighbours (node in the border lines have less number of one hop neighbors) to share information. According to the equation (5.12), following difference equation is considered for Spatio-Temporal Belief Vector generation filter.

$$\begin{aligned} Bel(B)(x,y,t,\theta) = \alpha_{0,0}Bel(B)(x,y,t-1,\theta_{0,0}) + \beta_{1,1}Bel(B|A)(x-1,y-1,t,\theta_{1,1}) + \\ \beta_{0,1}Bel(B|A)(x,y-1,t,\theta_{0,1}) + \beta_{-1,1}Bel(B|A)(x+1,y-1,t,\theta_{-1,1}) + \\ \beta_{-1,0}Bel(B|A)(x+1,y,t,\theta_{-1,0}) + \beta_{-1,-1}Bel(B|A)(x+1,y+1,t,\theta_{-1,-1}) \\ + \beta_{0,-1}Bel(B|A)(x,y+1,t,\theta_{0,-1}) + \beta_{1,-1}Bel(B|A)(x-1,y+1,t,\theta_{1,-1}) + \\ \beta_{1,0}Bel(B|A)(x-1,y,t,\theta_{1,0}) + \beta_{0,0}Bel(B|A)(x,y,t) \end{aligned} \tag{5.20}$$

Moreover, each sensor node calculates its gradient belief values from consecutive times at each time instance as follows,

$$m_{x_i,y_j} = \frac{\partial}{\partial t}(Bel(B|A)(x_i,y_j,t,\theta)) \tag{5.21}$$

θ can be determined from the m_{x_i,y_j} of all the neighbours.

$$\theta = \psi(m_{x_i,y_j}, Bel(B|A)(x_i,y_j,t,\theta)) \tag{5.22}$$

$\forall x_i, y_j$ are locations of neighbouring nodes

Since $0 \leq Bel(B) \leq 1$ and $0 \leq Bel(B|A) \leq 1$

$$\sum_{i,j=-1}^{i,j=1} \alpha_{i,j} + \sum_{i,j=-1}^{i,j=1} \beta_{i,j} = 1; \tag{5.23}$$

Based on our assumptions, when all the neighboring nodes are in the fire stabilized stage (severity magnitude is 1), we take the previous fire propagation direction or give more weight to the neighbour who has reached the stabilized stage earlier.

Therefore ψ is calculated as follows for the fire propagation scenario.

$$\psi(m_{x_i,y_j}, Bel(B|A)(x_i,y_j,t,\theta)) = \\ maximum(0.5.(Bel(B|A)(x_i,y_j,t,\theta))^2 + 0.5.(m_{x_i,y_j})) \quad (5.24)$$

$$\theta = maximum(0.5.(Bel(B|A)(x_i,y_j,t,\theta))^2 + 0.5.(m_{x_i,y_j})) \quad (5.25)$$

$\forall x_i, y_j$ are locations of the neighbouring nodes

Algorithms: Spatio-Temporal Evidence Filter-Severity Vector Generation

Data: Once the output of the Temporal Evidence Filter exceeds the given threshold any node can report it to the central node

```
if emergency message is received from the central node then
    if sampling timer fired then
        Sample all sensor signals ;
        Combine them to generate input Bel(B|A)(x,y,t) ;
        Perform local state space computation. Based on its input, past
        knowledge base and the inputs from neighbours ;
        Transmit the state vector Bel(B)(x,y,t,θ) to the neighbouring
        nodes
        if output Bel(B)(x,y,t,θ) greater than the threshold then
            Execute local actuation tasks if needed, based on the
            application ;
            Send event indication message to the base node ;
            Node goes to sleep ;
        else
            do nothing
        end
    else
        Node is in sleep state
    end
else
    Not an emergency
end
```

Algorithm 3: Distributed Spatio-Temporal Evidence Filter-Severity Vector Generation Algorithm

The algorithm runs in the central node is same as the Algorithm 2

The simulation setup is similar to section 5.4.6.

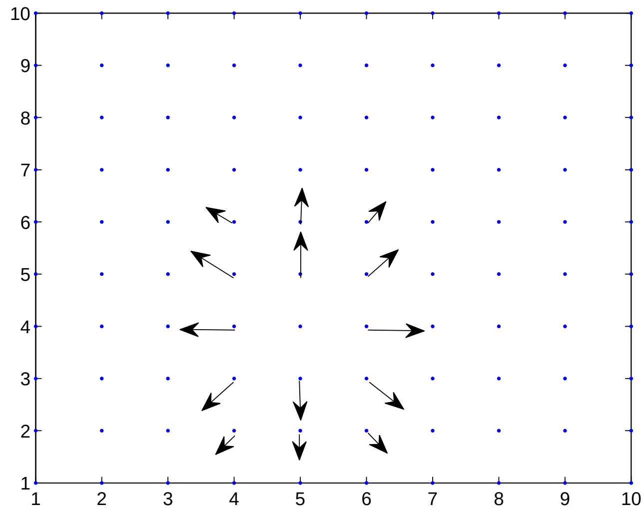


Fig. 5.23: Output states (magnitude and direction) of node, at time t=1s

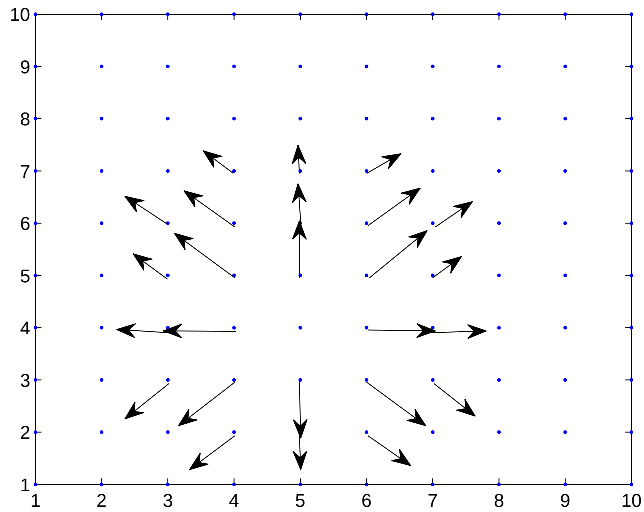


Fig. 5.24: Output states (magnitude and direction) of node, at time t=2s

5.4.8 Results Analysis of Spatio-Temporal Evidence Filter and Severity Vector Generation Filter

In the first part of the Spatio-Temporal Evidence Filter we introduced algorithms to estimate the severity level of an emergency based on the DS Information Filtering Framework. To save power, our algorithm initially starts with a Temporal Evidence Filter. Once an emergency is detected it will switched to Spatio-Temporal Evidence Filter. According to the fire initiation node, the network is dynamically

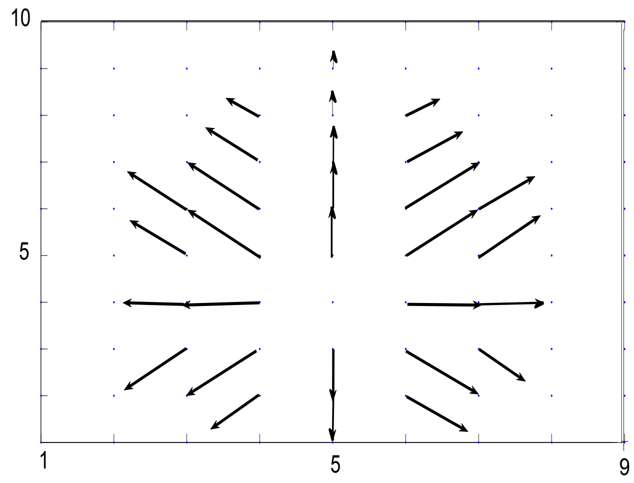


Fig. 5.25: Output states (magnitude and direction) of node, at time t=3s

divided in to regions (Figure 5.14). Based on the regions, each node communicates and assigns different weights to its neighboring nodes (neighbours who are from the fire initiation node may get higher confident weights). The DS Belief maps generated at the central node (base station) indicate the severity level propagation of the fire with space and time.

Moreover, in the second part, a severity vector generation algorithms have been introduced. Instead of dividing the network in to regions, we used a higher order filter to calculate the gradient of the severity magnitude. According to the gradient and the magnitude of the severity of the neighbouring node each node estimates the severity direction of the fire. Figures 5.23-5.25 show the directions of the fire propagation of nodes. Note that the severity vectors are plotted only for several selected nodes to make the figures clear. The results can be further refined to produce more accurate information on the fire propagation. Different fire propagation scenarios should be investigated to further enhance the accuracy of the severity belief vector. The severity vector can be successfully used to build a prediction model for emergency propagation.

Chapter 6

Selection of Filter Parameters Based on Error Variation

Selection of the filter parameters for the Evidence Filter is crucial. The poles and zeros determine the information bandwidth of the filter. Increasing the information bandwidth would eventually absorbs more noise in to the system, while making the system less sluggish to the new changes of the environment. The Dempster-Shafer Information Filter proposed in this thesis have two constrains on the filter coefficients,

$$Bel(B)(k) = \Sigma_{i=1}^{N}\alpha_i Bel(B)(k-i) + \Sigma_{i=1}^{N}\beta_i Bel(B|A)(k-i) \qquad (6.1)$$

where $\alpha_i, \beta_i \geq 0$ and $\Sigma_{i=1}^{N}\alpha_i + \Sigma_{i=1}^{N}\beta_i = 1$.

The above constraints are needed to ensure that the updated belief and plausibility constitute valid belief functions and plausibility functions according to Definition (2.1).

Selecting best filter parameters would strictly depend on the application. However in this chapter we will analyse and propose a range of filter parameters for emergency situations (considering fire propagation scenarios).

6.1 Simulation

6.1.1 Simulation Setup

The simulation setup is similar to section 5.4.1. We obtain data for three types of sensor modalities (temperature, smoke, optical density) attached to 36 sensor nodes deployed at the ceiling of the living room. Sensor readings were recorded over 1000 s. Smoldering type fire is considered.

6.1.2 Design Procedure

Each sensor node collects the multi-modality sensor readings and constructs the DS evidence table. The generated input evidence signal is then passed through a first order evidence filter (here we consider first order SISO Evidence Filter).

$$Bel(B)_1(k+1) = \alpha Bel(B)_1(k) + \beta Bel(B|A)_2(k) \tag{6.2}$$

Considering the fact that $\alpha = pole$ of the filter (no zeros), we varied the pole from 0.1-0.9. The procedure has been repeated 1000 times and the mean error values are obtained compared to the reference fire for each pole value. The reference fire signal is shown in Figure 6.1. Figure 6.2 shows an example output Evidence Signal.

6.1.3 Analyse the Filter Parameters Based on the Emergency Propagation Stages

To have an in depth analysis of the situation, the filter parameters were analysed based on regions of the fire propagation.

The regions are taken as follows,

- 1-100 s: Fire initiation stage
- 100-200 s: Fire growth stage 1
- 200-300 s: Fire growth stage 2
- 300-400 s: Fire growth stage 3
- 400-500 s: Fire stabilized stage 1
- 500-600 s: Fire stabilized stage 2
- 600-1000s: Fire stabilized stage 3

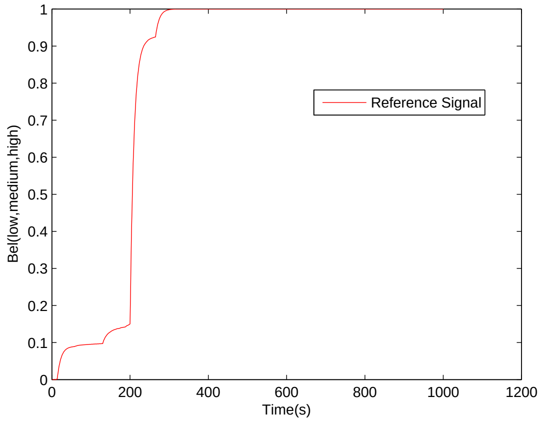


Fig. 6.1: Reference Signal with no noise

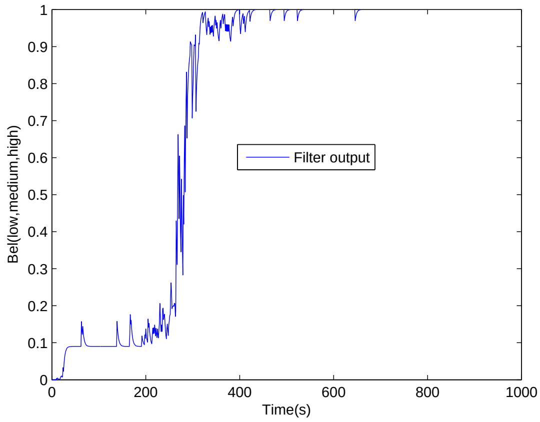


Fig. 6.2: Output Evidence Signal for a one case, α =0.8

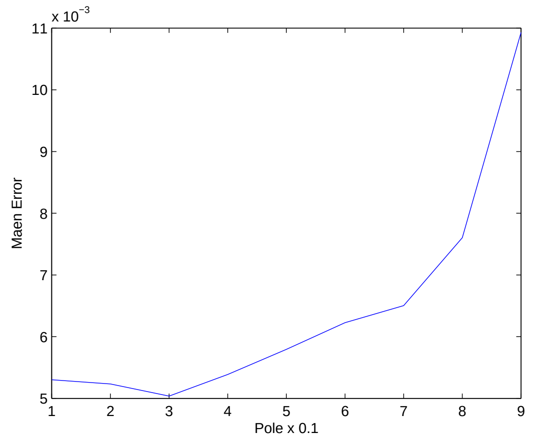


Fig. 6.3: Mean Error from 1s-100s vs Pole from 0.1-0.9

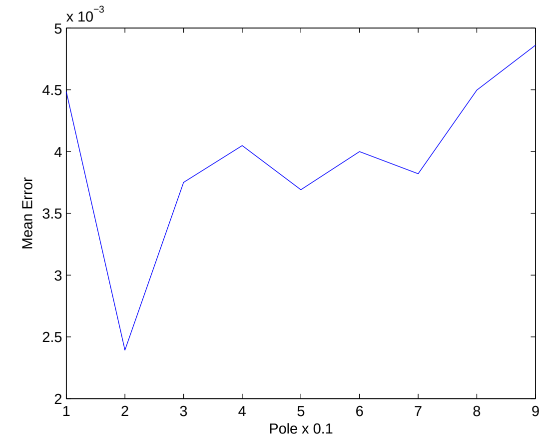


Fig. 6.4: Mean Error from 100s-200s vs Pole from 0.1-0.9

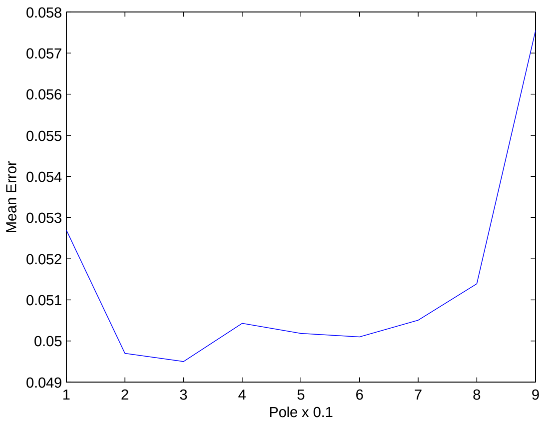


Fig. 6.5: Mean Error from 200s-300s vs Pole from 0.1-0.9

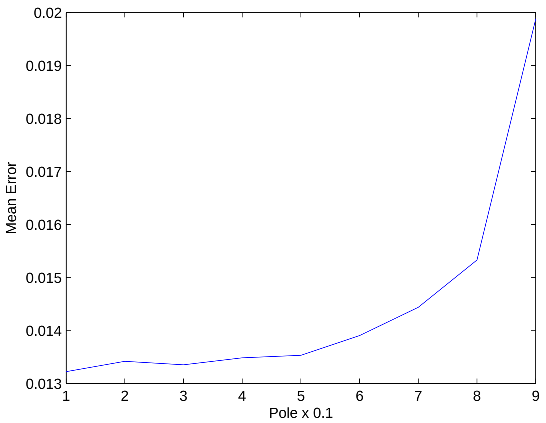


Fig. 6.6: Mean Error from 300s-400s vs Pole from 0.1-0.9

6.1.4 Results Analysis

During the fire ignition stage there is an ambiguity in the smoldering type fire at the beginning (smoke proceeds temperature and flame) (Figure 6.3). Therefore

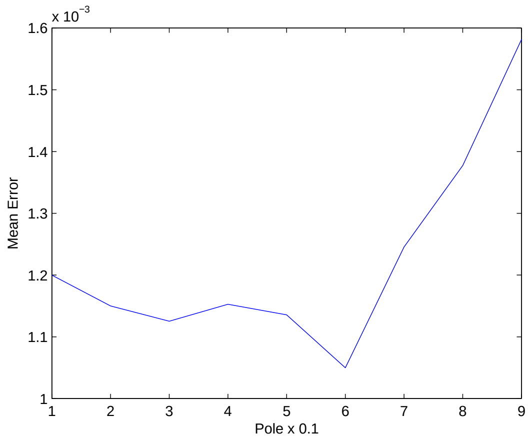


Fig. 6.7: Mean Error from 400s-500s vs Pole from 0.1-0.9

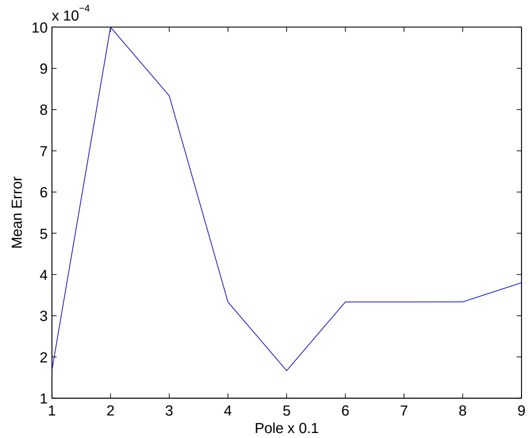


Fig. 6.8: Mean Error from 500s-600s vs Pole from 0.1-0.9

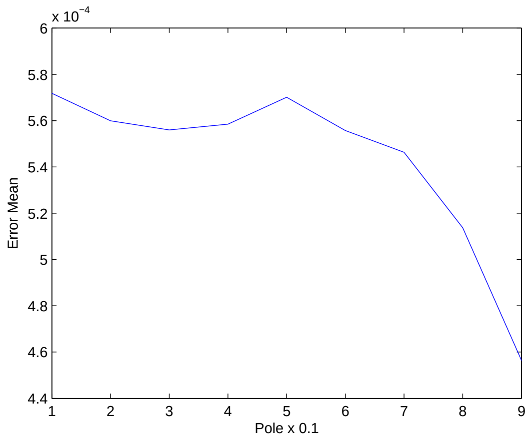


Fig. 6.9: Mean Error from 600s-700s vs Pole from 0.1-0.9

the filter produces more accurate output signal when the information bandwidth is widened (low pole). At the first stage of the fire growth, the ambiguity is more

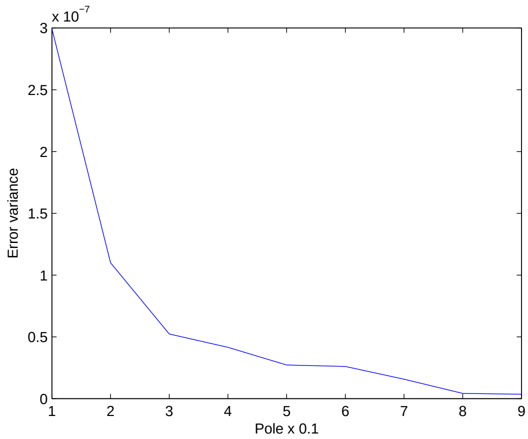


Fig. 6.10: Error variance from 1s-100s vs Pole from 0.1-0.9

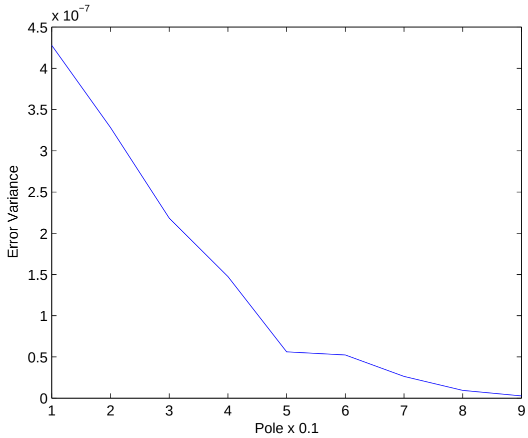


Fig. 6.11: Error variance from 100s-200s vs Pole from 0.1-0.9

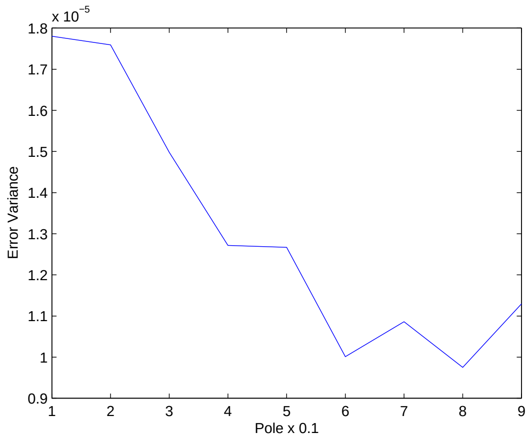


Fig. 6.12: Error variance from 200s-300s vs Pole from 0.1-0.9

higher as the temperature and the flame start growth in the severity while the growing rate of the smoke value get decreases and becomes stabilized. At this

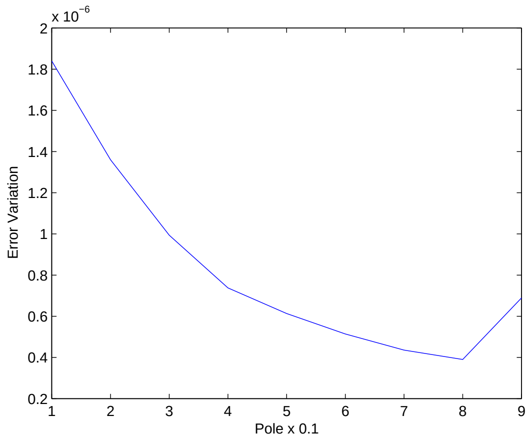


Fig. 6.13: Error variance from 300s-400s vs Pole from 0.1-0.9

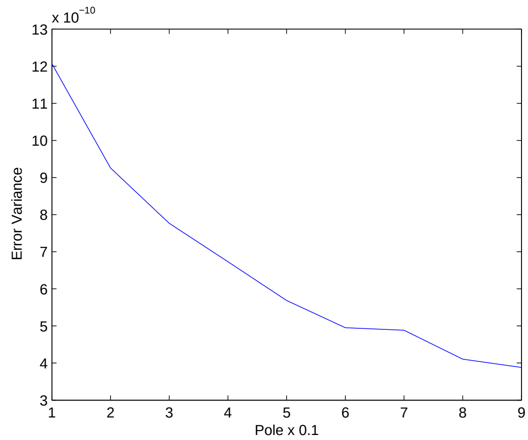


Fig. 6.14: Error variance from 400s-500s vs Pole from 0.1-0.9

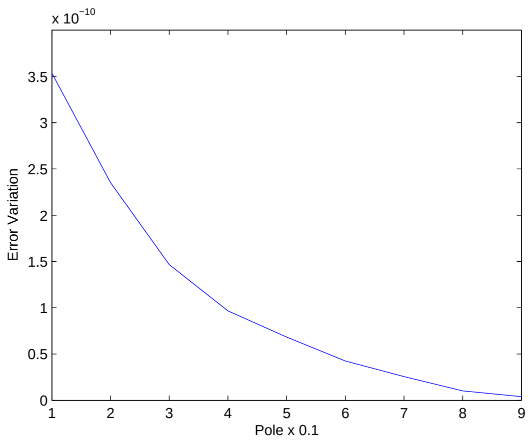


Fig. 6.15: Error variance from 500s-600s vs Pole from 0.1-0.9

stage output evidence signal is more accurate when the information bandwidth is higher than the previous stage (Figure 6.4). During the fire growth stage 2,

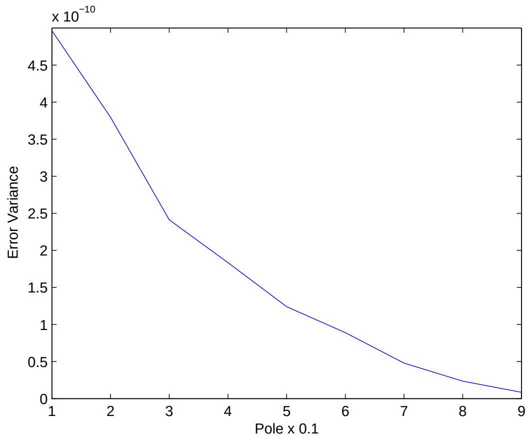


Fig. 6.16: Error variance from 600s-700s vs Pole from 0.1-0.9

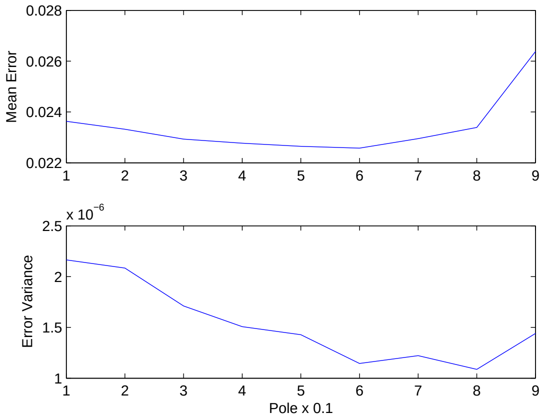


Fig. 6.17: Mean Error and Error variance from 1s-1000s vs Pole from 0.1-0.9

smoke has reached the maximum level and has stabilized while temperature and flame (optical density) has started growing rapidly. Therefore the pole is 0.3 for the minimum mean error (Figure 6.5). Final fire growth stage is more critical. In order to catch up with the rapid fire growth it is important to widened the information bandwidth (Figure 6.6). From 400s onwards fire starts getting in to a stabilized stage. Therefore making the filter to be more sluggish to the incoming evidence would make the filter absorbs less noise and more accurate (Figures 6.7-6.9). On the contrary, noise variance is less when the filter becomes more sluggish

Table 6.1: Noise Variation at each Stage

Mean, Variance	1-100s	100-200 s	200-300 s	300-400 s	400-500 s	500-600 s	600-1000 s
Pole for lowest Mean	0.3	0.2	0.3	0.1	0.6	0.5	0.9
Pole for lowest Variance	0.9	0.9	0.8	0.8	0.9	0.9	0.9

to the incoming evidence which is corrupted with noise (Figures 6.10-6.16).

Chapter 7

Conclusions

7.1 Dempster-Shafter Information Filtering

The work reported in this thesis develops the Dempster-Shafer Information Filtering framework for processing information from multiple sensor modalities. Essentially, DS Information Filtering offers a way of fusing information across multiple sensing modalities, time and space recursively. This concept is an extension of Evidence Filtering framework.

Temporal Evidence Filtering

Our main objective of removing noise in the clutter to minimize the uncertainty in the sensor measurements is achieved for greater extent by using both MISO and SISO Evidence Filters. The proposed DS Information Filtering framework was described with design procedures.

SISO Filter generates the input evidence signal by fusing the multi-modality sensor data. Any fusion technique can be used based on the DS theory. In this thesis we described Weighted averaging method and Evidence Updating method as the incoming evidence signal modelling technique. The MISO filter introduced in this thesis enables one to directly fuse and extract meaning from corrupted data gathered from multiple sensor modalities.

Practical use of the proposed concept was studied with a simulation example of an indoor fire spread application. Fire Dynamic Simulator was used to create an artificial residential fire in a living room. Measurements were taken from sensor nodes attached to the ceiling. Smoke, temperature and optical density measurements were initially corrupted with Gaussian noise. The DS evidences generated from the gathered data were sent through first order Evidence Filter (SISO and MISO). The output Evidence Signals clearly indicate the fire severity level with time at each node. Moreover, the results were compared with the Dempster-Shafer Evidence combination method. Our framework clearly outperforms the Evidence combination method. Matlab and FDS were used for simulation.

However coefficients can be determined dynamically during an emergency, in an indoor multi-storey building environment based on the delay of the link, residual node energy, building hierarchy etc. Therefore selection of time varying coefficients still needs to be investigated.

Spatio-Temporal Evidence Filtering

Temporal Evidence Filter enables each node to possess only partial knowledge on the environment under observation. However to process information more accurately and effectively each node should have a global knowledge on the environment. This can be achieved by extending the temporal evidence filtering to spatio-temporal evidence filtering. Each node generates a knowledge base using the evidences gathered from sensors attached to the node and the knowledge base of its neighbouring nodes.

This technique is used to produce severity level of an emergency in terms of severity magnitude and the emergency propagation direction (severity vector). Simulations were carried out targeting a fire spread model using a grid sensor network. The simulation results shown the belief maps generated using the outputs of the Spatio-Temporal Evidence Filters. It clearly indicates the knowledge about the fire propagation in a building. Here we used both Java and Matlab for simulation.

7.2 Error Variation with the Pole of Evidence Filter

The selection of filter parameters for the Evidence Filter is crucial and important. The initially proposed Evidence Filter has not address this aspect. The filter parameters are the confident given to the each evidence. This can be depended on the source of the evidence and the medium it is being transmitted etc.

However in this thesis we try to analyse the selection of the filter parameters based on the accuracy of the filter output when the noise is present. A simple first order SISO Evidence Filter was analysed when the multi-modality sensor data is corrupted with Gaussian noise. We can observe that depends on the growth stage of the fire, the pole value of the filter should be changed to get a more accurate output. Finally, it is basically compromising between sluggishness of the filter and absorbing less noise. At the fire initiating stage and the critical fire growth stage need a high information bandwidth (low filter pole). After the fire is stabilized, a narrow information bandwidth would absorbs less noise. Even though this makes the filter more sluggish it would not be a problem as for a considerable amount of time the filter produces a same output value. However we have not considered the fire ending phase. This should be further analyzed considering the total life cycle of a fire with many fire scenarios.

7.3 Severity Based Self-Organization Algorithm

We proposed a clustering algorithm suitable for emergency environment as well as non-emergency environment. SCAE uses the node residual energy and the node severity for decision makings such as CH selection, cluster formation, and CH rotation. Due to parameters considered in decision making, SCAE have been able to reduce the communication loss in the network. In addition, SCAE extends the network lifetime of WSNs by addressing the node failure issue and energy constraints during an emergency.

This section focuses on emergency situations which can calculate the severity values such as fire emergency, gas leakages, etc. However, in emergency situations like earthquakes, it will be hard to calculate the severity levels. Hence modifying the algorithm for such situations need to be investigated.

Note: This part of the research is a joint work and has been published in 2013 IEEE Eighth International Conference on Industrial and Information Systems.

7.4 Sensor Network Based Architecture for Emergency Response

We have proposed an Emergency Response and Navigation Architecture which supports rescuers to assist evacuees along safe paths while reducing the congestion and save trapped victims. In the proposed architecture - decision making in emergency response, and providing navigational support, acquires the required information from WSN and the knowledge manipulating system. The architecture provides a separate sub layer to distribute the relevant information to first responders and victims. This will help victims to navigate through the building even without the assistance of first responders. Also different firefighter job roles will get relevant information without any ambiguity.

In addition to the work proposed in this thesis, the connectivity between the knowledge manipulation layer and lower layers should be investigated. During an emergency this connection could be affected. Therefore an efficient and reliable connection topology should be identified. Also the proposed architecture mainly concerned on emergency detection and response, and navigational decision making. It needs to be further explored on other aspects like, providing users the information on highest possible time lines and if a transmission failure occurred, notify it to the user/aplplication as quickly as possible. Further a common data structure needs to be used with higher flexibility and proprietary formats. Communication topology , resource management, and security are some other aspects need to be looked over.

Note: This part of the research is a joint work and has been published in 2013 third International Conference on Information Communication and Management, World Academy of Science.

7.5 Summary of Key Contributions

1. A framework 'Dempster-Shafer Information Filtering' for processing multimodality sensor data with a high noise level, and novel distributed algorithms to implement Spatio-Temporal filtering applications in grid sensor networks are introduced. [39]

2. Design procedures for Temporal Evidence Filter (SISO and MISO) and Spatio-Temporal Evidence Filter (with belief vectors) were developed.

3. Selection of filter parameters for an emergency situation such as fire is analysed. Based on the severity stage of the emergency, the Best filter parameters were identified.

4. An optimised self organization algorithm was developed based on the proposed DS information framework and energy driven clustering algorithms. [34]

5. A sensor network based architecture for emergency response was developed. Some of the challenges in the emergency response were addressed. Localization, communication, self-organization of the sensor nodes were taken in to account with information processing in the Wireless Sensor Network. [40][41]

7.6 Publications

(a) D.M.Weeraddana, K.S.Walgama, and E.C.Kulasekere. Dempster-Shafer information filtering: temporal and spatio-temporal evidence filtering. Signal Processing, IEEE Sensors Journal

(b) D.M.Weeraddana, K.S.Walgama, and E.C.Kulasekere. Dempster-Shafer information filtering in multi-modality wireless sensor networks. World Academy of Science, Engineering and Technology, 79:644-651, 2013. [39]

(c) A. Guanathillake, D.M. Weeraddana, K.S. Walgama, and K. Samarasinghe. Self-organization of wireless sensor networks based on severity of an emergency environment. In Industrial and Information Systems (ICIIS), 2013 8th IEEE International Conference on, pages 483-488, Dec 2013. [34]

(d) S. Gayan, D.M.Weeraddana, and A. Gunathillake. Sensor network based adaptable system architecture for emergency situations. In Lecture Notes on Information Theory, volume 2, No 1, pages 85-91, March 2014. [40]

(e) D.M.Weeraddana, A.Gunathillake, and S.Gayan. Sensor net-work based emergency response and navigation support architecture. Inter-national Journal of Electrical, Electronic Science and Engineering, 79:2-7, 2013. [41]

Appendix A

Self-Organization of Wireless Sensor Networks Based on Severity of an Emergency Environment

In this section, we propose an optimized self-organizing algorithm named *Severity based Clustering Algorithm for Emergency* (SCAE) to prolong the network lifespan during an emergency. The severity status of the emergency is used with the residual energy of the nodes during self-organization of the network . The estimation of the severity is obtained by filtering the Dempster-Shafer (DS) belief values which are generated from multi-modality sensor data. To our knowledge, there is no existing self-organizing algorithm to address challenges during an emergency situations to improve the quality of the WSN.

A.0.1 Related Work

A variety of clustering algorithms have been proposed for prolonging the life of WSN. This section reviews some of the most relevant algorithms to our research.

LEACH [19] is an energy efficient adaptive clustering protocol proposed for periodical data gathering applications in WSN. As an extension, SEP [20] was introduced. Both are simple, does not need large overheads and the nodes make decisions, but randomly select few sensor nodes as Cluster Heads (CH) which leads to non uniform cluster formation. HEED [21] periodically selects CHs according to their residual energy to avoid the non uniform cluster distribution but it uses a complex weight based cluster setup procedure. Moreover, these algorithms use a time based CH rotation mechanism. EDAC [22] has an energy based CH selection and rotation mechanisms. Here cluster boundaries do not change with time. Chang [42] proposed an ECRA to maximize the lifetime of the network. Clustering, data transmission, and intra-CH rotations are the three phases in this algorithm.

Gamwarige et al. [6] proposed another energy-driven clustering algorithm EDCR to avoid most of the problems in clustering algorithms. This uses the residual energy of sensor nodes for selection and rotation of CHs. Furthermore the paper [43] proposed an algorithm with novel re-clustering method which can further optimize the energy usage in the network. EEUC [44], EDUC [45] tries to address the issues in CHs closer to the BS by proposing unequal clustering mechanism.

However there is a lack of clustering algorithms proposed in literature to deal with an emergency situations. This part of the research proposes a self-organizing algorithm to address the node failure issue in an emergency environment. Moreover, SCAE focuses on the lifetime of the network.

A.0.2 Network Model

Here we consider a sensor network consisting of N number of randomly deployed sensor nodes. The same energy consumption model proposed by previous cluster based sensor network algorithms [6, 44, 22, 45, 42, 19, 20, 21, 43, 46] is adopted. A sensor node consumes E_{elec} energy at the transmitter or receiver circuitry and $\mathcal{E}_{amp}$ energy at the transmitter amplifier. A sensor node expends $E_{Tx}(l, d)$ or $E_{Rx}(l)$ energy in transmitting or receiving a l bit message to or from distance d respectively. These can be computed using equations (A.1) and (A.2). Furthermore, the energy for data aggregation in CH node is E_{DA}.

$$E_{Tx}(l, d) = E_{elec} \times l \; + \; \mathcal{E}_{amp} \times l \times d^n \tag{A.1}$$

$$E_{Rx}(l) = E_{elec} \times l \tag{A.2}$$

where n corresponds to radio propagation path loss exponent.

Some reasonable assumptions are made to simplify the network model. They are,

1. Base Station does not have any energy limitations.

2. Nodes and the BS are stationary after deployment.

3. Nodes can use power control to vary the amount of transmission power.

4. Computation power of the node is negligible compared to transmitting and receiving power.

5. Links are symmetric.

A.1 Details of the Algorithm

The main objective of the SCAE is to minimize the communication loss due to node failures in an emergency environment. This is achieved by delaying the CH failures in the network and allocating less priority to non-CH nodes to select their CH which might get dropped from the network quickly. Here, a measurement called severity is used to find out the level of the emergency and this is incorporated with clustering algorithm to make decisions. SCAE consists of five phases: Estimating the severity level of an emergency phase, Cluster Head (CH) candidacy phase, Cluster formation phase, Data gathering phase and CH rotation phase. The detail description of each phase has discussed in following subsections.

A.1.1 Estimating the Severity Level of an Emergency Phase

The main objective of this part of the algorithm is to accurately estimate the emergency level. In our previous work (Chapter 5) we proposed a framework to estimate the severity level of an emergency situation using Dampster-Shafer formalism and Evidence Filtering. WSNs with multiple sensor modalities are considered to increase the accuracy of the results. The proposed DS belief filtering framework is capable of extracting useful information buried in the raw data gathered from multiple sensor modalities. If the state of the environment under observation is defined as x_i, time instances as t_i, space coordinates as θ_i, and modalities as s_i, then the Dempster-Shafer Frame of Discernment (FOD) is defined over states under observation,
$DS\ FOD=\{x_1, ...x_n\}$

Firstly DS belief and/or plausibility values should be generated according to the data obtained from each sensor modality. Each sensor-modality generates a separate evidence signal by obtaining evidences according to equation (A.3).

$$\lambda_{t_k} = f(\zeta_{s_i,t_k}) \tag{A.3}$$

Where function f can be any evidence combination method.

Then Multiple Input Single Output (MISO) Evidence Filter will be used to filter out important signal components from unwanted noise in the raw sensor data.

$$Bel(B)(t) = \Sigma_{k=1}^{M} \alpha_k Bel(B)(t-k) + \Sigma_{i=1,k=0}^{N,M} \beta_{s_i,k} Bel_{s_i,k}(B|A)(t-k) \tag{A.4}$$

$$Pl(B)(t) = \Sigma_{k=1}^{M} \alpha_k Pl(B)(t-k) + \Sigma_{i=1,k=0}^{N,M} \beta_{s_i,k} Pl_{s_i,k}(B|A)(t-k) \tag{A.5}$$

$$\alpha_k \geq 0; \beta_{s_i,k} \geq 0 \tag{A.6}$$

$$\Sigma_{k=1}^{M} \alpha_k + \Sigma_{i=1,k=0}^{N,M} \beta_{s_i,k} = 1; \tag{A.7}$$

The conditions in equations (A.6) and (A.7) are to ensure that the belief and plausibility functions constitute valid DS functions.

During the information filtering, the filter updates the existing knowledge base with the new evidence while taking into account the inertia and integrity of its already available knowledge. Coefficient α is the weight given to the available knowledge while β is the weight given to incoming evidence.

The output of the MISO Evidence Filter provides a reasonable indication on the severity of the emergency. Each sensor node in the network runs this MISO filtering and sends the output at each time step to the cluster head.

A.1.2 Cluster Head Candidacy Phase

The most suitable CHs are selected in this phase. Current researches interested only on the residual energy of the node while selecting the CHs. However in an emergency the key parameter is not only the energy of the node. The parameter, severity of the node, also need to be considered. In an clustering algorithm most crucial role is CH. Hence, in SCAE, a node with highest energy and less severity is selected as the CH.

Initially, all sensor nodes consider themselves as potential candidates of being a CH. The sensor nodes receive a CH advertisement from any other sensor node will abandon their quest to become a CH. Each node i transmit its residual energy $E_{res,i}$ to its neighborhood. Then node i calculates the maximum energy $E_{rel\_max,i}$ as

$$E_{rel\_max,i} = \max\left\{ \max_{j \in N_i^R} E_{res,j},\ E_{res,i} \right\} \tag{A.8}$$

where N_i^R corresponds to set of nodes within a neighborhood of maximum radius R from node i. Then the sensor node i transmit its candidacy message within a neighborhood of radius R at a time instance $T_{candi,i}$ given by equation (A.9)

$$T_{candi}(i,t) = T((1 - P(i,t))(1 - \gamma) + \gamma Bel(i,t)) \ + \ K_i \tag{A.9}$$

where T is the limited time interval for CH candidacy phase, $\gamma \in \ [0, 0.5]$ is a random time unit, $P(i,t) \in \ [0,1]$ represents the relative position of the node i with respect to the other nodes in it's neighborhood R in terms of its residual energy level, $Bel(i,t)$ represents the severity of the CH at time instance t and K_i is a random time unit. K_i is introduced to reduce the possibility of collision among sensor node advertisements with identical $P(i,t)$ and $Bel(i,t)$ in the same neighborhood. $P(i,t)$ value for sensor node i is given by equation (A.10).

$$P(i,t) = \frac{E^t_{res,i}}{E^t_{rel\_max,i}} \tag{A.10}$$

A.1.3 Cluster Formation Phase

In this phase, node j which is not a CH selects the most suitable CH i as it's CH. For the CH selection, non-CH nodes consider three things; residual energy of the CH, distance to the CH, and severity of the CH. Hence, to select its CH_j node j uses the equation (A.11)

$$CH_j = \left\{ i | \max_{i \in \ H \cap N_j^R} CHPriorityValue(i,j) \right\} \tag{A.11}$$

$$CHPriorityValue(i,j) = \begin{cases} \frac{E^t_{res,i}}{(1+Bel(i,t))}\frac{P_{rx_{i,j}}}{P_{tx,i}} & Bel(i,t) > 0 \\ E^t_{res,i}\frac{P_{rx_{i,j}}}{P_{tx,i}} & Bel(i,t) = 0 \end{cases} \tag{A.12}$$

where H represents the all set of CHs, $E^t_{res,i}$ represents the residual energy of CH i at time instance t, $P_{rx_{i,j}}$ represents the received signal power from node i to node j, $P_{tx,i}$ represents the transmitted power of the advertisement message for node j and $Bel(i,t)$ represents the severity of CH i at time instance t.

After the CH candidacy time interval, node j selects it's CH CH_j. Subsequently, CHs calculate the TDMA schedule for the nodes who joined its cluster and broadcast the schedule among them. Apart from the slots allocated for each member node in its cluster, the TDMA schedule will have a separate time slot reserved for the CH to send any messages to its members such as control messages, acknowledgement messages, etc. All the member nodes will keep awake during this time slot to identify if there are any control messages from the CH.

A.1.4 Data Gathering Phase

The nodes use single hop communication with their CHs, and the CHs communicate with the BS. Each member node awakes in its allocated time slot and transmit data. During other time slots it goes to idle mode. The CH uses a data aggregation algorithm to merge the received data from its cluster member nodes before sending to the BS to reduce the amount of unwanted or repetitive information transmitted to the BS.

A.1.5 CH Rotation Phase

Energy usage of CH is comparatively higher than the non CH nodes and they die very quickly. Hence rotation of CH role is needed to balance the energy usage of the network. In addition to that in an emergency, nodes might be dropped from the network due to physical damage etc. If a CH drops from the network, all it's member nodes can not communicate further until re-clustering occurs. Therefore the number of CHs dropping from the network need to be minimize or delay. By considering these factors, SCAE examines two conditions in CH rotation. One is whether the residual energy drops below a threshold value and the second one is whether the CH's severity value goes beyond a predefined threshold value. However there is a restriction on severity based CH rotation to avoid occurrence of continuous re-clustering i.e. if CH i goes for a severity based CH rotation, and after sometime the same node i has chosen as a CH, it will not consider the severity based CH rotation. The reason is that in CH candidacy and cluster formation phases, the severity value of the node has been considered and a less priority is given to such nodes to become a CH. If a node with high severity value has elected as CH, it implies that, all it's neighbour nodes also have a higher value for severity.

If a CH identifies it needs to go for a CH rotation phase, it transmit a triggering message to base station. Subsequently the BS will inform this to all other CHs. Then all CHs use their immediate next chance in the TDMA slot to communicate this fact to its neighborhood, and further request nodes to send their residual energy along with the data in its allotted slot. Finally CH i computes the maximum residual energy component of its cluster and transmit to it's neighbours.

A.2 Simulation Results

The performance of SCAE was evaluated using MATLAB. First, Fire Dynamic Simulator was used to develop a fire scenario and DS information filtering was applied to estimate the severity of the fire. Then, examines the CH selection and the performance of SCAE was examined in an emergency situation. Finally, we illustrate how SCAE prolong the network lifetime.

The simulation energy parameters set as E_{elec} at 50 nJ/bit, $\mathcal{E}_{amp}$ at 100 pJ/bit/m^2 and E_{DA} at 5 nJ/bit/message. Advertisement or setup packets were chosen 60 bits in length and normal data packets were chosen to be 2000 bits long. Area of the network was considered as 50 m $\times$ 50 m and total number of nodes was 73. For the simulation, it assumes that the severity calculation frequency and data transmitting frequency are same. Furthermore, transmission range of each CH was chosen to be 13m.

A.2.1 Simulation Setup

Fire scenario is developed using Fire Dynamic Simulator (FDS) which is developed by National Institute of Standard and Technology (NIST), United States [38]. In the simulation set-up which is shown in Figure A.1, the sensor nodes were deployed at the ceiling. Each sensor node is attached with three sensors, to sense temperature, smoke, and optical density. At t=0, ignition starts and reading were taken for 1000s.

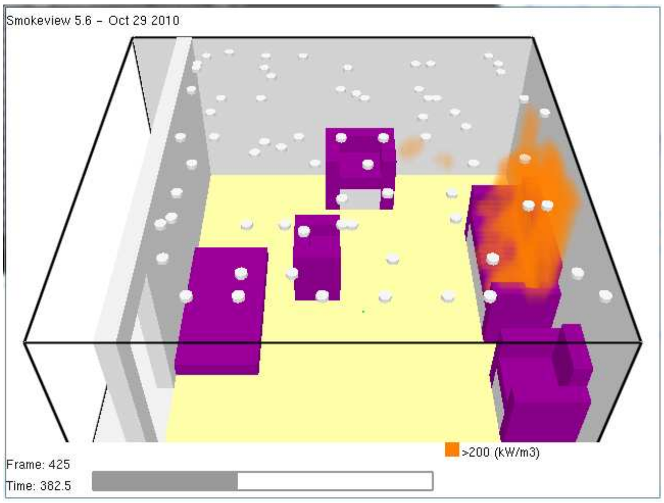


Fig. A.1: Simulation setup: Living room, Sensor nodes are deployed at the ceiling

A.2.2 Applying DS Information Filtering to Estimate the Severity of the Fire

In order to detect an emergency and determine the growth stage of the fire or the severity level, the DS Frame of Discernment (FOD) is defined as,
$DS\ FOD(\Theta)$=$\{$$no\ emergency$, $low_1, low_2.., low_n, medium_1, medium_2, ..$ $medium_m, high\}$
If $m = n = 1$, number of hypothesis is $2^4 = 16$.
At each time instance, each sensor node takes measurements for temperature, smoke, optical density and assigns masses to respective DS hypothesis.

Gathered evidences for multiple modalities are separately ordered over time and separate input evidence signals are generated. Multiple signals are passed through first order MISO LTI Filter.

$$Bel(B)(t) = \alpha_t Bel(B)(t-1) + \Sigma_{i=1}^{n} \beta_{t,s_i} Bel_{s_i}(B|A)(t) \quad \text{(A.13)}$$

$$Pl(B)(t) = \alpha_t Pl(B)(t-1) + \Sigma_{i=1}^{n} \beta_{t,s_i} Pl_{s_i}(B|A)(t) \quad \text{(A.14)}$$

Same weights were given to existing knowledge base and new evidences from multiple sensor modalities by assigning α_t= 0.5, and β_{t,s_1}= β_{t,s_2}= β_{t,s_3}= $\frac{1-\alpha_t}{3}$. In

Table A.1: Selected CH's Residual Energy and Belief Values

Time = 1s		Time = 300s		Time = 500s		Time = 700s	
SCAE	EDCR	SCAE	EDCR	SCAE	EDCR	SCAE	EDCR
01(0.0000/0.4987)	01(0.0000/0.4987)	03(0.6345/0.3544)	06(0.1326/0.4453)	15(0.6345/0.3705)	15(0.6345/0.4213)	09(1.0000/0.4003)	23(1.0000/0.3073)
04(0.0000/0.4991)	04(0.0000/0.4991)	14(0.1226/0.3852)	11(0.1377/0.4474)	19(1.0000/0.3069)	29(0.9999/0.4202)	18(1.0000/0.3596)	36(1.0000/0.3692)
07(0.0000/0.4983)	07(0.0000/0.4983)	24(0.1040/0.3670)	25(0.0000/0.4489)	31(0.6563/0.3671)	48(0.1000/0.4248)	32(1.0000/0.3431)	58(1.0000/0.3630)
18(0.0000/0.4994)	18(0.0000/0.4994)	26(0.0000/0.3849)	35(0.0000/0.4554)	35(0.1219/0.3595)	50(0.1690/0.4181)	68(0.5925/0.3989)	69(1.0000/0.3532)
19(0.0000/0.4987)	19(0.0000/0.4987)	34(0.0000/0.3840)	37(0.9948/0.4408)	46(0.1350/0.3508)	51(1.0000/0.3740)	-	72(1.0000/0.3945)
23(0.0000/0.4989)	23(0.0000/0.4989)	41(0.1000/0.4093)	45(0.0000/0.4522)	65(0.1213/0.3948)	65(0.1213/0.4267)	-	-
51(0.0000/0.4992)	51(0.0000/0.4992)	67(0.0000/0.3799)	46(0.0000/0.4379)	70(0.1000/0.3964)	70(0.1000/0.3652)	-	-
71(0.0000/0.4996)	71(0.0000/0.4996)	71(0.0000/0.3979)	73(0.1000/0.4529)	72(0.1523/0.3984)	71(0.1728/0.4013)	-	-
*Format of data : CH ID(Belief Value/Residual Energy)							

both cases A is taken as the $DS\ FOD$ (Θ).

A.2.3 Cluster Head Selection of the Algorithm

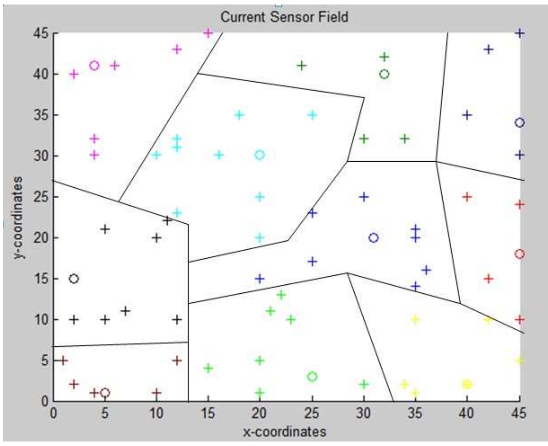
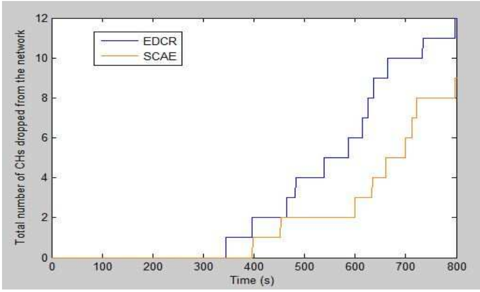


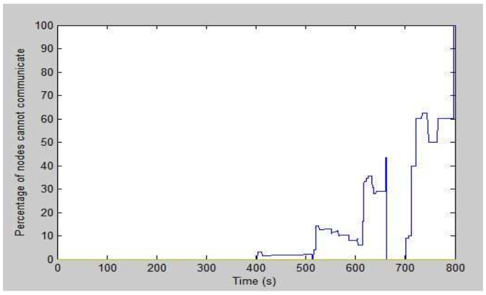
Fig. A.2: CH distribution over the network

To optimize the energy usage of the network, CHs need to be distributed all over the network. Figure A.2 shows the CH distribution of SCAE. According to the figure, SCAE have been able to distribute the CHs all over the network. Also, Table A.1 illustrate the effect of CH selection in this algorithm. For the comparison, EDCR algorithm [6] was selected because of it's good CH distribution.

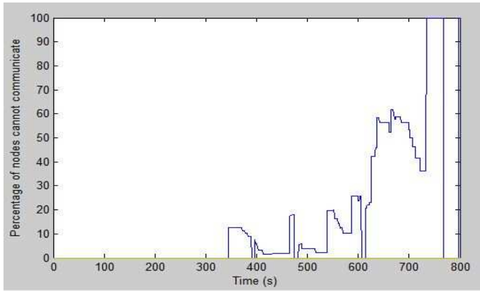
According to the data in Table A.1, SCAE has given a higher priority value for the nodes with less severity to be elected as CHs compared to EDCR. Initially, both algorithms have chosen the same nodes as CHs because at that stage there is no emergency and belief values are zero. However when time passes, the severity values of nodes increases and CH selection was different. For example, at time=300s SCAE has selected CH with higher energy and less severity. But EDCR has selected CH with higher severity i.e. node CH_ID=37. Therefore this CH drops from the network very quickly and its member nodes fail to communicate further. Furthermore, at time=700s, EDCR has selected CHs with higher



(a) SCAE & EDCR algorithms number of CHs failed



(b) SCAE algorithm's percentage of communication failure



(c) EDCR algorithm's percentage of communication failure

Fig. A.3: Performance of the algorithm in an emergency

severity values, but SCAE has selected CH with less severity whereever possible (CH_ID=68).

Finally, with the CH selection equation used in SCAE, it has been able to select the best CH with highest residual energy and less severity value.

A.2.4 Performance of the Algorithm in an emergency environment

To examine the performance of SCAE, one assumption was made, that the sensor node drops from the network when it's severity value reaches one. With this assumption, number of CHs dropped from the network was calculated with the time. Then due to those CH failures, number of alive nodes can not communicate further was calculated as a percentage of nodes in the network. The simulation results were shown in Figure A.3

According to Figure A.3a, SCAE's CHs start to fail 56s later than EDCR. Eventhough it starts at 400s, at 600s only two CH has dropped, but in EDCR it was five CHs. Also in Figure A.3b and Figure A.3c illustrate the percentage of nodes loss their communication due to CH failure. In SCAE it was negligible until

500s, but in EDCR it was 10% at time 344s. Furthermore, in EDCR algorithm 100% communication failure can see from time 741s to 767s, but at that time there was nearly 55% communication failure with SCAE.

Finally, because of the CH selection and CH rotation mechanism used in SCAE, it has been able to reduce and delay, the failures of CHs in the network. Due to the cluster formation equation, the percentage of nodes that cannot continue to communicate has reduced in SCAE.

A.2.5 Energy Efficiency of the Algorithm

In this section, it is assumed that nodes will not drop from the network until nodes energy goes to zero. In order to present the comparison of SCAE with EDCR, free space propagation model were considered with a network of 73 nodes. Each node contains 0.5J energy and randomly distributed over a region of 50 $\times$ 50 with BS located at (25,25).

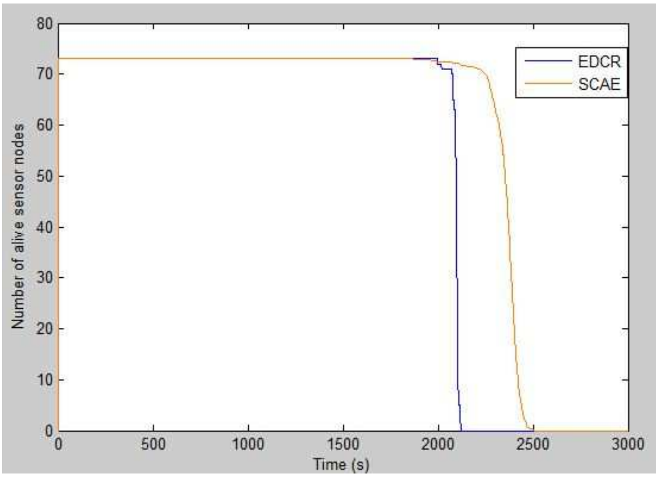


Fig. A.4: Energy efficiency of the algorithm

Figure A.4 shows number of sensor nodes remaining alive with respect to the time. From the results obtained, SCAE has optimized the energy usage in the network than EDCR in all three lifetime measurements listed in [6, 43].

Finally, from all the results obtained SCAE has outperformed EDCR algorithms. The reason for the outperforming is the novel methods used in CH selection, Cluster forming and CH rotation.

Appendix B

Sensor Network Based Architecture for Emergency Response

B.1 Introduction

According to the statistics of New York 9/11 incident, approximately 400 firefighters died during the rescue operation and the total death was estimated to be over 6000. The number of victims could be reduced if a rich emergency navigation system would have been deployed. Emergencies such as fire, gas leakages, earthquakes, tsunamis, terrorist attacks bring long lasting suffering to any community. Due to the severe loss of human lives and valuable assets in an emergency situation, there is an increasing interest in developing emergency navigation systems with the aim of minimizing the severity of the impact caused by an emergency.

First responders offer immediate help to victims in case of an emergency. During the different phases of a rescue operation, the responsibilities of first responders will be shared among several important job roles, which vary depending on the complexity of the incident. During a typical fire emergency, those job roles can be identified as incident commander (IC) who coordinates the overall emergency response, firefighter who directly involves with emergency and sector commander (SC), Crew Commander (CC) etc [23]. Different job roles need information only specific to their responsibilities for emergency response and navigation. Moreover, the victims in the emergency situation also need assistance to exit from the emergency, if the support from first responders is not available or get delayed.

WSN is an attractive option for indoor environments today, due to the recognition of the importance for energy conservation [6] and emergency/rescue operations [25] [47]. While sensor networks can be installed in new buildings at the time of construction, they can also be easily installed in older buildings due to their wireless nature. WSNs require that a large number of sensors be positioned easily and that they configure themselves to perform the tasks needed without human intervention.

Recently navigation with wireless sensor networks (WSNs) has become the most heated debated research area. WSNs raises many exciting opportunities to minimize the impacts caused by emergencies [23] [24] [25] [26]. These studies show the benefits of a sensor network to support Emergency Response (ER) and navigation.

Unfortunately there is a lack of coherence among research that has been reported for emergency support area. Correct decision making from the corrupted data gathered from the WSN, energy efficiency of sensor nodes [6], routing of data through sensor networks, localization of nodes [48] and self-configuration of sensor nodes in a network [49] are the most important aspects in emergency response, which is not properly addressed in a common WSN architecture.

A proper design architecture for a wireless sensor network is crucial in the development of systems for complex and dynamic environments such as emergency response, especially when the WSN is deployed in a multi-story building. Therefore, in such a domain, architecture based on accurate design could prevent many disasters.

B.2 Related Work

The work reported in [25] proposes a high-level architecture of the system that is capable of deploying the human computer interfaces suitable for supporting various fire fighter job roles during a fire ER. Moreover, it has gathered actual information, requirements from first responders, these information was highly useful when gathering basic knowledge on emergency environments in our research. Work presents in [50] proposes a system architecture for emergency management mainly addressing network topology, configuration, data management in the ER. CodeBlue [24] is a framework explores the use of WSN in ER including medical care. However the navigation support for victims and firefighters is not addressed in above mentioned systems. Moreover, these researches are mainly concerned with data capturing, decision making and presentation. Localizing and optimizing the network parameters (i.e. communication delays, retransmission rate) are not captured in the above researches.

B.3 Challenges in an Emergency Response Environment

The nature of an emergency is highly dynamic and demanding. Real-time data retrieval, processing and management is required.

Sensor node failures, communication link failures and noise added to the multi-modality sensed data are common challenges in WSNs which introduce uncertainties in the overall system. Communication time delays directly impact on real-time data retrieval and also introduce errors in the estimation of dynamically varying environment.

During an emergency, first responders may add stationary and mobile sensor nodes to the WSN. Integrating and tracking the newly added nodes is also a challenge.

Basically during an emergency following major challenges can be highlighted.

- Highly dynamic and demanding environments
- Real-time data retrieval,processing and management
- WSN may loose its existing sensor nodes or add new sensor nodes to its network during an emergency
- Communication link failures
- Noise added to the multi-modality sensed data
- Communication time delays

However, the resources for computation and communication may be limited at an incident site. Therefore, meeting the demanding performance requirements under resource constraints is a challenge.

B.4 Proposed Architecture for Emergency Response

The proposed layered architecture shown in Figure B.1 consists of three major layers. Namely, WSN Perceiving and Prediction layer, Navigation Support layer, and Knowledge Manipulation layer. These will collaboratively function to create a complete WSN which can be adaptable for emergency situations and support rescue and navigation operations. Each layer consists of sub layers as described further in following sections.

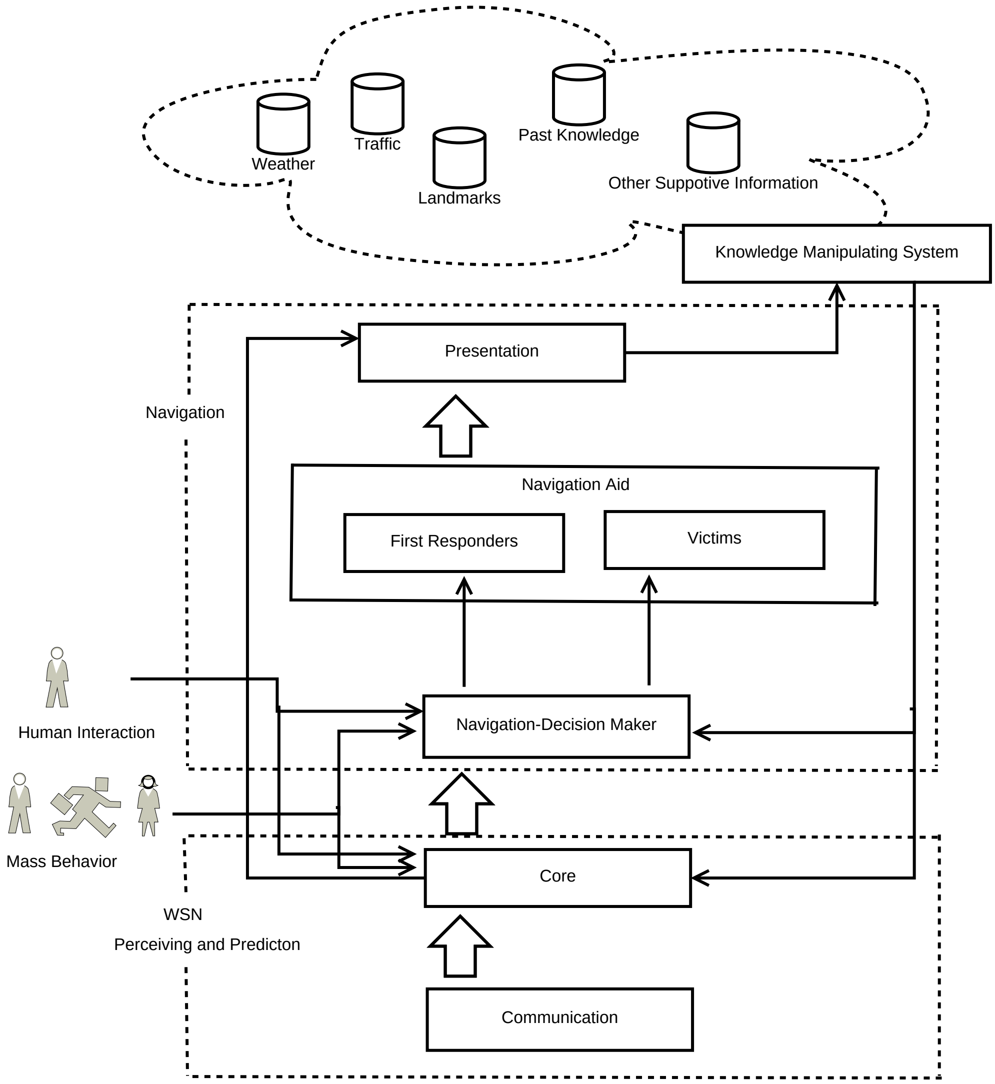


Fig. B.1: Proposed Emergency Response and Navigation Support Architecture

B.4.1 WSN Perceiving and Prediction layer

The system will function in two main states normal and emergency, where the former describes the functionality of the system under non-emergency situations and the later describes the functionality of the system under emergency conditions where several adjustments are needed to be done.

WSN perceiving and prediction layer shown in Figure B.2 consists of three major sub layers namely, the communication layer, the core layer, the presentation layer which will collaboratively function to create a complete WSN which can be adaptable for emergency situations. Each layer consists of sub layers as described below.

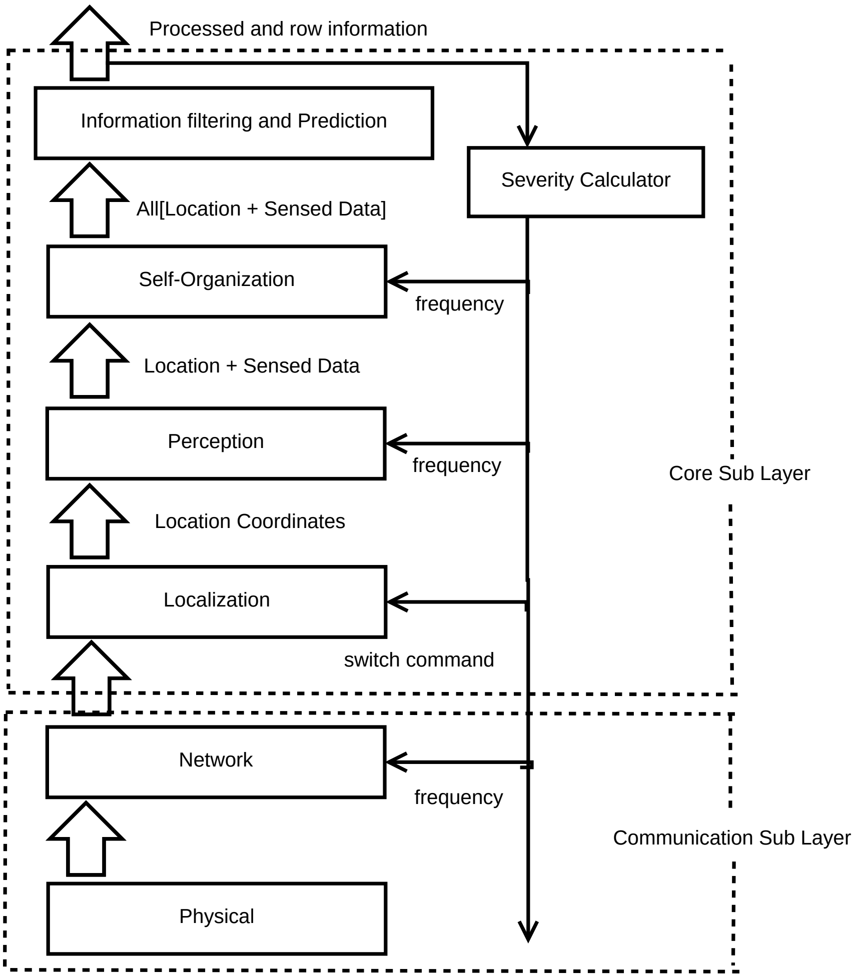


Fig. B.2: Proposed Architecture

Communication Layer

Physical and Medium Access Controller layers These layers are responsible for the physical arrangements of sensor nodes and communication among them including medium access. Sensor nodes deployment topology, power levels, frame rates and antenna arrangements are few major things to be considered.

Core Layer

The output of the communication layer feeds as the input to the core layer and passes relevant fused and predicted messages to the presentation layer.Core layer consists of five sub layers, the localization layer, the perception layer, the self-organization layer, the data filtering and prediction layer and the severity calculator layer. Detailed description of following layers is in [40].

Localization This is the layer where the sensor nodes will be located with either absolute or relative coordinates. Since the environment is indoor and dynamic it is more suitable to use a distributed localization algorithm with range-free techniques. Then the location information will be passed to the upper layer Perceiving to combine with environment sensed data as shown in Figure B.3.

Perception This layer will collect all the data generated at the sensor nodes. The data will be a collection of information such as temperature, humidity, air quality, smoke and so on of the monitoring environment. This perceived date will then be combined with location information and passed on to the upper layer for further processing. Figure B.4 shows an overview of the layer.

Self-organization This is the layer where clusters are created dynamically. All the sensor nodes within cluster will communicate with their local cluster head first and only the cluster heads will communicate with the upper layer there after. This process will efficiently contribute to save the energy or power of the whole WSN. Perceived data combined with location will then be passed to the upper layer for further processing. Figure B.5 shows an overview of the layer.

Data filtering and prediction This is the layer where the data manipulation and calculations take place. It uses the received data from the lower layer as inputs and provides predictions on dynamically varying situations using knowledge based algorithms developed based on Dempster-Shafer formalism. Depending on the output of this layer several actions will be taken. The processed data will then be passed to both the presentation layer and the severity calculator. Figure B.6 shows an overview of the layer.

Severity calculator Provides feedbacks to the sub layers in order to adapt the system. In this layer most of the important parameters such as network refreshing rate, perceiving rate, clustering rate will be set. On the other hand it will switch the node localization algorithms if there is an emergency. Figure B.7 shows an overview of the layer.

After calculating the severity index of the environment, whole system will get reconfigured if there exists an emergency. For an example if there is a medium strength fire, then the system will adapt to that by changing its refreshing rates, moving to a different localization algorithm and perceiving the environment more frequently until the environment become normal. This process will repeatedly run throughout the system.

Presentation Layer

Presentation This layer is responsible for taking the necessary actions according to the output of the data filtering and prediction layer. Conditions of the environment could be presented as an easily readable map. On the other hand this layer could be used to inform the conditions of the environment to relevant parties(i.e.first responders) if an emergency is taken place.

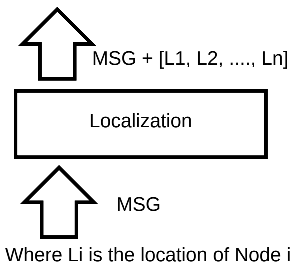


Fig. B.3: Function of Localization Layer

B.4.2 Navigation Support Layer

This architecture focuses on, an indoor emergency environment in which several dangerous areas can exist which are threats to human safety such as fire, smoke,

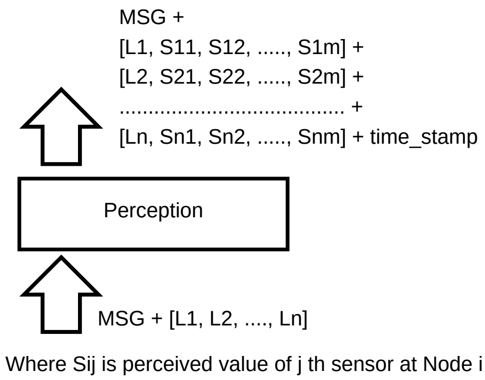


Fig. B.4: Function of Perceiving Layer

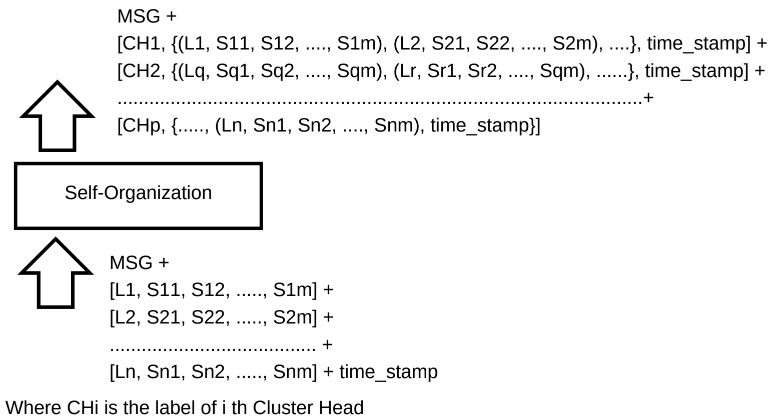


Fig. B.5: Function of Self-organization Layer

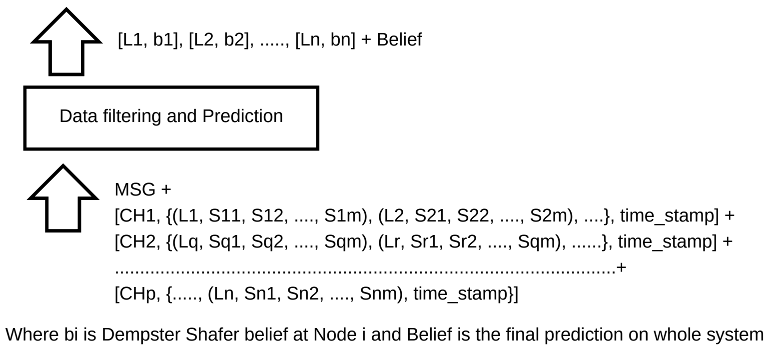


Fig. B.6: Function of Data Filtering and Prediction Layer

obstacles, etc. Thus, people need to evacuate from the building as quickly as possible while keeping away from those dangerous areas. Also first responders need to have an idea of emergency's spreading in the building and the locations of trapped people. Hence, the main objective of this layer is supporting the victims to evacuate from the building and navigate responders through the building to find their way to save human lives and combat emergencies.

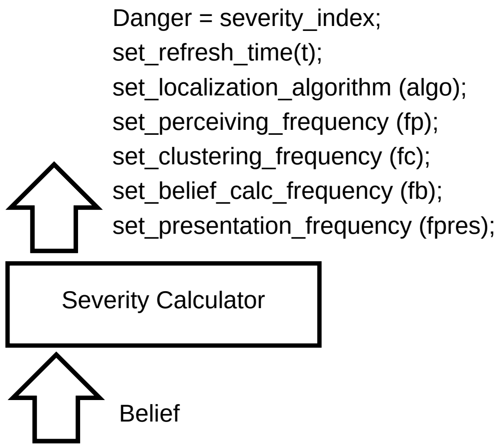


Fig. B.7: Function of Severity Calculator Layer

Navigation support layer consists of three sub layers. Navigation-Decision Maker, Navigation Aid, and Presentation. This layer gets the input from the WSN Perceiving and Prediction layer, knowledge manipulation layer and human behaviors. Then the output displays on a Graphical User Interface (GUI). Also, some of the decisions made in navigation aid sub layer are stored in knowledge manipulation layer.

Navigation-Decision Maker Sub Layer

The main role of this sub layer is dividing the processed data receiving from the WSN Perceiving and Prediction layer, knowledge manipulation layer, human interaction, and human mass behavior to, two navigation aid sub sections. Moreover, the data needed for the first responder navigation algorithm and the victim navigation algorithm are different. Therefore, the main objective of this sub layer is according to the rules specified, make decisions and separate the processed data into two categories. Then pass this information to two navigation sub layers respectively.

Navigation Aid Sub Layer

The main objective of this sub layer is providing navigation information to both first responders and victims. Navigation aid sub layer gets information from navigation-decision maker and output of its display in presentation sub layer. Also, decisions made on this layer stored in knowledge manipulation layer via the presentation sub layer. This sub layer consist of two sub sections namely first responders and victims.

First Responder Sub Section

Use of body area network (BAN) for first responder navigation has become more important in order to fight with the incident and save human lives. The dangers associated with this activity are the result of a number of factors, such as lack of information regarding first responders (i.e. location and health state), the environment surrounding (i.e. spread of emergency, temperature) and mental and physical stress in an emergency environment [51].

Indoor navigation of first responders deals with guiding them from its present location by avoiding obstacles and hazardous regions to save human lives and combat hazards. Hence, these navigation algorithms need information such as environment characteristics (heat, smoke, dust etc.), hazardous areas, locations, real-time map of the building, trapped people and etc. This information is fed to the first responder subsection from navigation-decision maker sub layer. With this information the navigation algorithms proposed in [51][52] can be performed to guide the first responders.

The decisions made by this layer, stored in the knowledge manipulation layer via presentation sub layer for future use. Also the output of navigation algorithm is passed onto the presentation sub layer to guide the first responders.

Victim Sub Section

In an emergency, victims may hard to find a way out from the building because of hazardous areas or other obstacles. As at any time, any spot may turn dangerous. Therefore providing navigation information only for first responders to exit from hazardous areas is not enough. As a result, finding safe and efficient escape paths for victims under dynamically changing environmental is the main objective of this sub section.

In this subsection, it takes the input from the navigation-decision maker sub layer which contains information on hazardous areas, emergency spreading, congestion areas etc. and can perform navigation algorithms proposed in [26][53].The decisions made by this subsection, stored in the knowledge manipulation layer via presentation sub layer for future use. Also the output of navigation algorithm is passed onto the presentation sub layer to guide the victims.

Presentation Sub Layer

The presentation sub layer is responsible for displaying the processed information in a GUI and taking the necessary actions. In normal state without an emergency, the conditions of the building environment (temperature, humidity, color etc.) can be presented in an easily readable building map. If an emergency is taken place, this layer can be used to inform the conditions of the environment to relevant parties (i.e. first responders). Also during an emergency, presentation sub layer is responsible of displaying navigation information to victims through LCD displays or lighting bulbs and transferring navigation information to first responders through BAN or other relevant way.

Moreover, all the outputs receiving from core sub layer and navigation aid sub layer (output of first responder and victim sub sections) are displayed in a meaningful manner to make the correct decision on the situation.

B.4.3 Knowledge Manipulation Layer

Addition to the information from WSNs, the information gathered from various other data sources such as traffic data, atmospheric conditions, information regarding important locations etc.[25], can be used to make the whole emergency response system more accurate and efficient.

In this layer, we introduce several possible components to manipulate knowledge gathered from several sources. Dynamically varying results of this layer are sent back to the core layer and to the navigation layer to further refine the results at each layer. This layer will be deployed in a central location, to gain knowledge on disaster management of a particular geographical region. The connectivity between Knowledge Manipulation Layer and other layers in the architecture can be accomplished by using any suitable communication methods, via gateways.

The main objective and aim of this layer is to support emergency response and navigation by providing a rich collection of knowledge to the system.

Information of Road Traffic

Once an emergency alert is received and confirmed at the rescue operations center, the response time of the first responders towards the emergency situation is very critical. Providing real-time and forecasted road traffic related information appropriately to the firefighters would improve the response time effectively. By retrieving the real time and forecasted traffic information, fire fighters will be able to find the most suitable path to the emergency location and reach immediately. This information can be stored in a database and update dynamically.

Information of Atmospheric Conditions

First responders can acquire valuable insight knowledge on the incident site by getting dynamic information related to atmospheric conditions in the vicinity of an incident. According to this information firefighter can capture nearly accurate surrounding environment of the emergency site, and take relevant equipments and human resources to the site immediately. Moreover, forecasting on the propagation of the emergency (i.e. spread of fire according to the wind speed) is possible and evacuating the relevant other surrounding crowds (who are not in the emergency site currently) is also possible.

Information of Important Surrounding Locations

Information about the nearest hospitals, lakes and other water sources, dangerous locations (i.e. power plants, chemical storages) is very important to the first responders in order to make correct and immediate decisions on emergency response. Especially according to this information the resources they supply to the emergency site will be varied. This information will be stored in the database and most probably will be static.

Knowledge from Past Emergencies

Information about the past emergency incidents will be saved in a database. The perceived past knowledge can be used and combined with the current emergency information to further refine the knowledge of the incident. Forecasting on future emergencies and filtering current noisy information during an emergency can be achieved.

Information Gathered from Various Websites

There may be important websites to get more information on the emergency environment. The websites can be previously identified as important websites or real time search results on the web. Web mining technologies can be incorporated into this part to extract meaningful information related to the incident.

Knowledge Manipulating Framework

The algorithm(s) run in this framework should be able to retrieve information from various sources and update the relevant databases. Moreover, it will provide information to various layers and components in the system when needed. In a nutshell this framework adds following services to this layer,

- Retrieve information from various sources and update the databases.
- Distribute raw information to relevant layers when the raw information is needed.
- Manipulate, combine [54] [55] all the information gathered in real time and provide more detailed knowledge to relevant parties/layers when needed.
- Forecast on the event of interest and provide information to relevant parties/layers when needed.

Efficient maintenance of a large database system, saving, retrieving, managing large sets of data real time and off line is crucial to optimize the response time in an ER.

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