Dempster–Shafer Information Filtering Framework: Temporal and Spatio-Temporal Evidence Filtering

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***Abstract*— This paper presents an information processing framework for distributed sensor networks. The framework is capable of directly processing temporally and spatially distributed multimodality sensor data to extract information buried in the noise clutter. Moreover, we introduce distributed algorithms to implement spatio-temporal filtering applications in grid sensor networks within the context of the framework. The proposed framework is based on the belief notions in Dempster–Shafer (DS) evidence theory and evidence filtering method. Further analysis is done by exploiting a fire propagation scenario when high noise is present in the sensed data. We compare intuitively appealing results against DS fusion method to grant further credence to the proposed framework.**

***Index Terms*— Dempster–Shafer belief vectors, Dempster-Shafer formalism, evidence filtering, multi modality sensor fusion, severity of emergency, wireless sensor network.**

I. 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].

The emergence of WSNs has shed light on creation of new smart sensor systems, which can be useful to enhance the quality of human lives. The reliability of information gathered from sensor networks is extremely important since important actions are usually taken based upon the sensed information. Hence, the cost of any unreliable information can be very significant especially when it is used for critical decisions (firefighters in their rescue operations) or activation of actuators. 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 situations [2]. The decisions made based on the fused information range from estimating location or velocity of an object, identifying and distinguishing different sates 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).

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Therefore, 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 sensor nodes after initial deployment. Moreover prior information, conditional probability, joint probability distributions are not available. There are many advantages of using Dempster-Shafer theory in such scenarios. Most importantly the DS method relaxes the Bayesian method's restriction on mutually exclusive hypotheses; if no prior information is available we can avoid assigning probabilities to singleton propositions. Evidence Filtering [3], [4] is capable of fusing multi-modality evidences to directly infer on frequency domain. Therefore the properties in the DS theory and the Evidence Filtering are highly important in our context. However the noise buried in the information clutter has never been addressed in Evidence Filtering technique.

The framework we propose in this paper is based on the Dempster-Shafer theory [5] and the Evidence Filtering framework [3], [6]. Within the framework, sensor node fuse information over time internally, exchange and fuse among peer nodes to obtain local viewpoints about the environment under observation. The central node is competent to build global belief maps about the scenario. Moreover, our current work is focused on introducing techniques to extract information for handling random noise buried in the information clutter.

From the application point of view, we address a WSN deployed in a multi-storey 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 of the proposed framework.

II. Dempster-Shafer Information Filtering

The temporal order Dempster-Shafer (DS) Information Filtering framework was initially introduced in [7]. Within the context of DS information filtering, we proposed MISO and SISO LTI filtering techniques for information fusion in WSNs. The work reported in [8] uses the DS Information Filtering framework (Temporal Evidence Filter) for self-organization of sensor nodes based on the severity of an emergency. In this paper we further 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 further enhance the knowledge possessing process of a sensor node.

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, DS FOD $= \{x_1, \dots x_n\}$.

A. Temporal Evidence Filtering

The detailed description of the Temporal Evidence Filtering can be found in [7]. This is an extension of the Evidence Filtering framework [3]. We will briefly describe the SISO and the MISO Evidence Filtering in this section.

1) Single Input Single Output Evidence Filter: Input evidence signal to SISO Evidence Filter is modeled using two methods, the weighted averaging method fused 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 fuse using any DS evidence combination methods [4].

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

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

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.

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

(2) Dempster-Shafer Evidence Combination:

$$\zeta_{s_i,t_k} = g(X_{s_i,t_k}) \tag{2}$$

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.

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

Where function f can be any evidence combination method, several popular methods to combine evidences are presented in [9] 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 event of interest B as follows, by ordering the fused evidence λ over time.

$$I(t) = Bel(B)(t) \text{ or } I(t) = Pl(B)(t)$$

$I(t)$ is the input evidence signal. The notations Bel and Pl are derived from DS theory and referred to belief and plausibility functions. B is a hypothesis consists with one or more states x_i.

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

$$\begin{aligned} Bel(B)(t) = &\sum_{i=1}^{N} \alpha_i Bel(B)(t-i) \\ &+ \sum_{i=1}^{N} \beta_i Bel(B|A)(t-i) \end{aligned} \tag{4}$$

2) Multiple Input Single Output Evidence Filter: Each sensor-modality generates a separate input evidence signal by obtaining evidences according to 2.

$$\begin{aligned} Bel(B)(t) = &\sum_{k=1}^{M} \alpha_k Bel(B)(t-k) \\ &+ \sum_{i=1,k=0}^{N,M} \beta_{s_i,k} Bel_{s_i,k}(B|A)(t-k) \end{aligned} \tag{5}$$

where $\alpha_k \geq 0$; $\beta_{s_i,k} \geq 0$, $\sum_{k=1}^{M} \alpha_k + \sum_{i=1,k=0}^{N,M} \beta_{s_i,k} = 1$

During the information filtering, filter updates the existing knowledgebase 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.

B. Spatio-Temporal Evidence Filter

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 about the environment. This can be achieved by extending the Temporal Evidence Filtering to Spatio-Temporal Evidence Filtering.

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

- Higher order difference equation

$$\begin{aligned} &Bel(B)(x, y, t) \\ &\quad = \sum_{i=1} \sum_{j=1} \sum_{k=1} \alpha_{i,j,k} Bel(B)(x-i, y-j, t-k) \\ &\qquad + \sum_{a=1} \sum_{b=1} \sum_{c=1} \beta_{a,b,c} Bel(B|A)(x-a, y-b, t-c) \end{aligned} \tag{6}$$

- State space models: Fornasini-Marchesini (FM) and Givone-Roesser State Space Models FM model [10] for 3-D is given by,

$$\begin{aligned} X(x, y, t) = &A_{011} X(x, y-1, t-1) \\ &+ A_{101} X(x-1, y, t-1) \\ &+ A_{111} X(x-1, y-1, t-1) \\ &+ B_{010} U(x, y-1, t) \\ &+ B_{100} U(x-1, y, t) \\ Y(x, y, t) = &CX(x, y, t) + DU(x, y, t) \end{aligned} \tag{7}$$

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 [11].

C. Spatio-Temporal Evidence Filtering With Belief Vectors

The Spatio-Temporal and Temporal Evidence Filtering frameworks produce Dempster-Shafer belief values consisted 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 an 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).

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.

$$\begin{aligned}
&Bel(B)(x, y, t, \theta) \\
&= \sum_{i=1}\sum_{j=1}\sum_{k=1}\sum_{l=1}\alpha_{i,j,k,l}Bel(B)(x-i, y-j, t-k, \theta-l) \\
&\quad + \sum_{a=1}\sum_{b=1}\sum_{c=1}\sum_{d=1}\beta_{a,b,c,d}Bel(B|A) \\
&\quad\quad \times (x-a, y-b, t-c, \theta-d) \qquad (8)
\end{aligned}$$

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

$$m_{x_i,y_j} = \frac{\partial}{\partial t}(Bel(B|A)(x_i, y_j, t, \theta)) \qquad (9)$$

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

$$\theta = \psi(m_{x_i,y_j}, Bel(B|A)(x_i, y_j, t, \theta)) \qquad (10)$$

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

III. Experimental Scenario for Fire Spread Model

A. Simulation Setup: Temporal Evidence Filtering

Fire scenario is developed using Fire Dynamic Simulator (FDS) which is developed by National Institute of Standard and Technology (NIST), United States [12].

A living room consists with one couch seat cushions, two couch armrests and one couch back cushions. 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, where initially generates less flame and heat with more smoke. A grid based sensor network is deployed at the ceiling consists with 36 (9×4) sensor nodes. Each sensor node is attached with three sensors, to sense temperature, smoke, and optical density. At t=0, ignition starts. Fig. 1 shows the simulation setup in FDS smoke view. Sampling time is set to 1s.

At each time instance, each sensor node takes measurements for temperature, smoke, optical density and assigns masses to respective DS hypothesis.

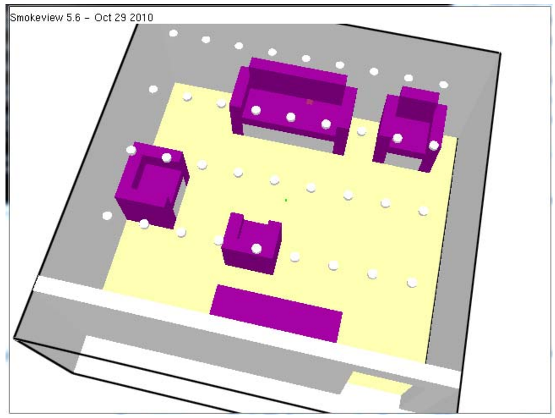

Fig. 1. Simulation setup: Living room, sensor nodes are deployed at the ceiling.

TABLE I
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	$m_{l,m,h}$	$m_l + m_m + m_h + m_{l,m}+$ $m_{m,h} + m_{l,m,h}$	$m_l + m_m + m_h+$ $m_{l,m} + m_{m,h} + m_{l,m,h}$ $+m_{n,l}$

a) Noise: A zero mean white Gaussian noise is added to raw sensor measurements of temperature, smoke and optical density.

B. Mass Assignment and Construction of the Evidence Table

Normalized sensor measurements are obtained at each time instance 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 (I) is constructed to generate input evidence signals. Below abbreviations are used in the above table.

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*, $m_{m,h}$ = 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.

C. Sensor Fusion

1) SISO Evidence Filter: Gathered evidences for multiple modalities are fused using DS evidence updating method.

$$Bel(B)(t) = \alpha_t Bel(B)(t-1) + \beta_t Bel(B|A)(t) \qquad (11)$$

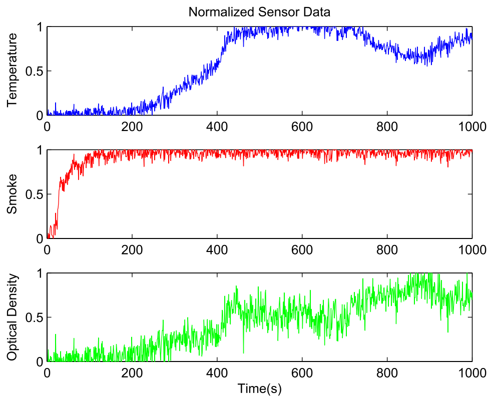

Fig. 2. Normalized sensor measurements at node 32 before noise is added.

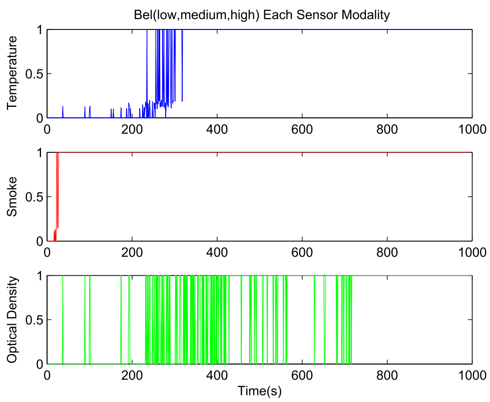

Fig. 3. Input evidence signals of MISO Filter at node 32.

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

2) MISO Evidence Filter: Gathered evidences for multiple modalities are separately ordered over time and separate input evidence signals are generated.

$$Bel(B)(t) = \alpha_t Bel(B)(t-1) + \sum_{i=1}^{n} \beta_{t,s_i} Bel_{s_i}(B|A)(t) \quad (12)$$

A narrow information bandwidth is taken, by assigning a high value to α_t. Lets take $\alpha_t = 0.9$, and $\beta_{t,s_1} = \beta_{t,s_2} = \beta_{t,s_3} = \frac{1-\alpha_t}{3}$. In both cases A is taken as the DS FOD (Θ).

D. Results Analysis of Temporal Evidence Filtering

Fig. 2 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. 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. 3. 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. 6.

Basically in both cases fusing over time has provided more reasonable indication of the fire scenario with less ambiguity

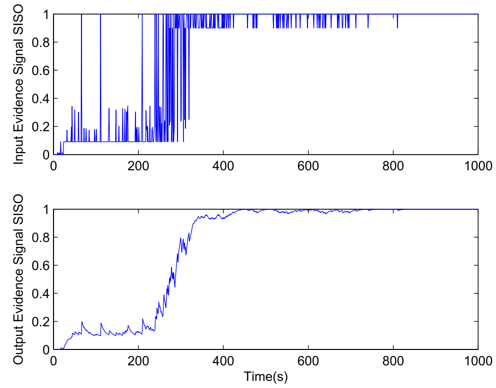

Fig. 4. Input versus output evidence signals of SISO filter at node 32.

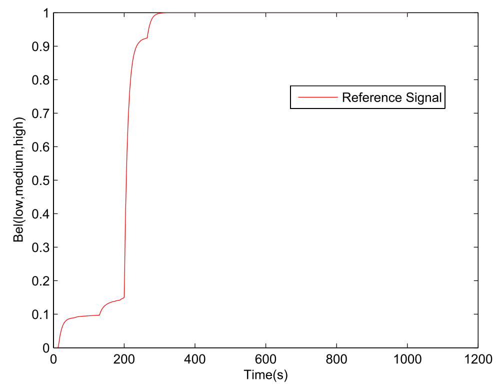

Fig. 5. Reference fire signal.

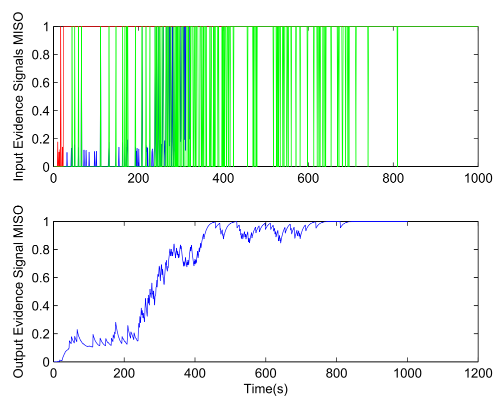

Fig. 6. Input versus output evidence signals of MISO filter at node 32.

for dynamically varying states when the noise is present. Fig. 4 and Fig. 6 compare input and output evidence signals of both filters (Fig. 5 illustrates the reference fire signal when no noise is present). The outputs from all three methods (SISO, MISO and DS evidence combination) are shown in Fig. 7. The error variation with respect to time in both DS combination output and SISO, MISO Evidence Filter output is shown in Fig. 8. Mean errors/ error variances for DS combination and Evidence Filter are shown in Table II. According to the results obtained, the proposed methods clearly outperform the DS evidence combination.

At the beginning of the fire we can observe a sudden increment in the output signal, next there is sluggishness due

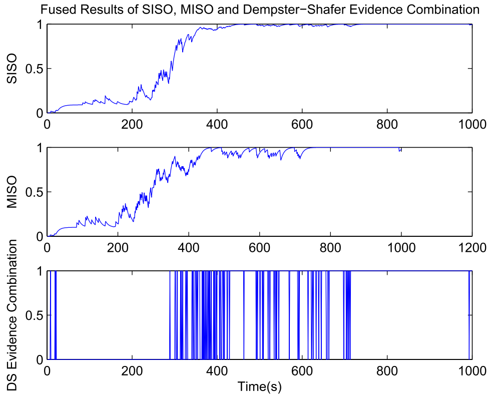

Fig. 7. DS combination and SISO evidence filter outputs at node 32.

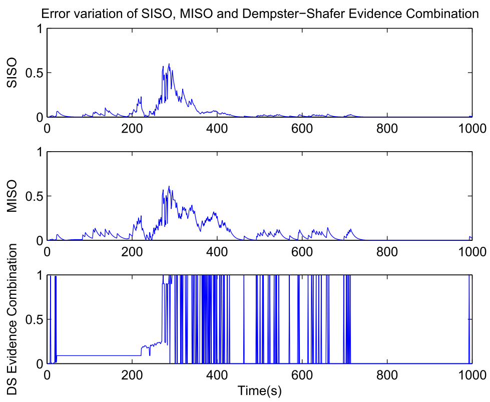

Fig. 8. Error variation of DS combination and SISO evidence filter output at node 32.

TABLE II
RESULTS COMPARISON

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

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 knowledgebase 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. 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.

E. Spatio-Temporal Filtering to Estimate the Fire Severity

The algorithm developed in this section is focused to estimate the severity state of the fire/gas distribution in a building using a grid sensor network.

Same algorithm runs on all the nodes and the decision making algorithm runs in the central node. Once an emergency occurred, 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 individual sensor nodes.

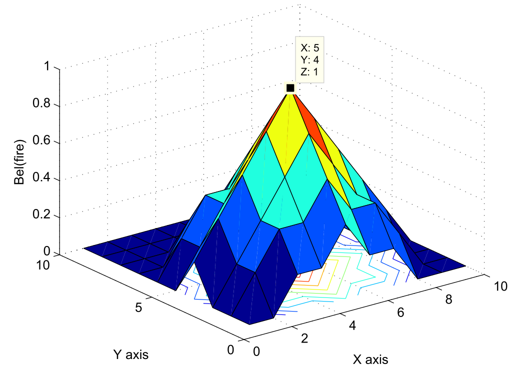

Fig. 9. Output states of the each node in the network, at time t = 1s.

Following FM state space equation is considered for Spatio-Temporal Evidence Filter

$$\begin{aligned} X(x,y,t) &= A_{011}X(x,y-1,t-1) \\ &\quad + A_{101}X(x-1,y,t-1) \\ &\quad + A_{111}X(x-1,y-1,t-1) \\ &\quad + B_{011}U(x,y-1,t-1) \\ &\quad + B_{101}U(x-1,y,t-1) \\ &\quad + B_{111}U(x-1,y-1,t-1) \\ &\quad + B_{000}U(x,y,t) \\ Y(x,y,t) &= CX(x,y,t) \end{aligned} \tag{13}$$

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.

a) Algorithms (spatio-temporal evidence filter): All the nodes run the same distributed algorithm (see Algorithm 1) to estimate the severity.

F. Simulation Setup: Spatio-Temporal Evidence Filter

A grid sensor network with 100 nodes, 10 × 10 in size is considered. The distance between each two nodes is considered to be same and 1m. 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 Fig. 9-13 are taken for 1ms 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.

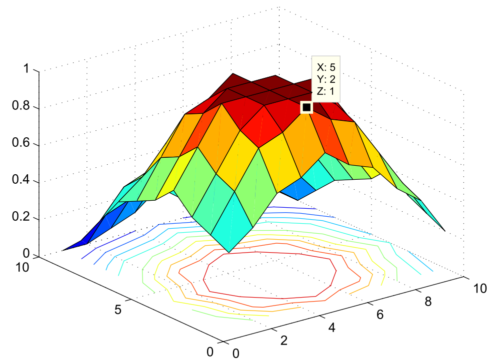

Fig. 10. Output states of the each node in the network, at time t = 3s.

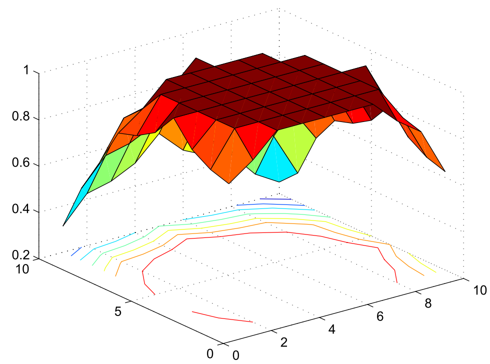

Fig. 11. Output states of the each node in the network, at time t = 5s.

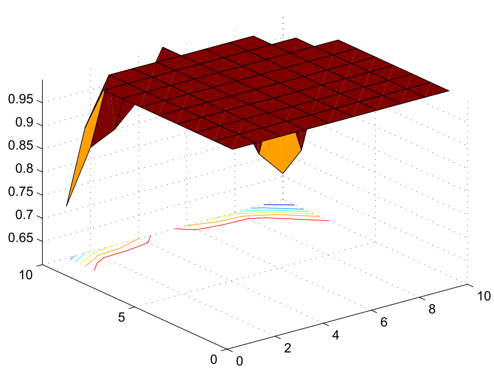

Fig. 12. Output states of the each node in the network, at time t = 7s.

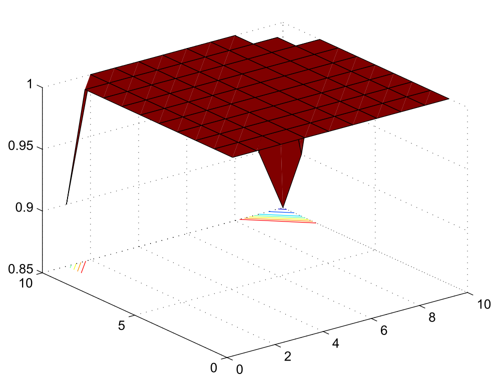

Fig. 13. Output states of the each node in the network, at time t = 8s.

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

G. 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 focuses 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 occurred, 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-Temporal Belief Vector 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 individual sensor nodes.

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 (nodes in the border lines have less number of one hop neighbors) to share information. According to the equation (8), following difference equation is considered for Spatio-Temporal Belief Vector generation filter.

$$
\begin{aligned}
&Bel(B)(x, y, t, \theta)\\
&= \alpha_{0,0} Bel(B)(x, y, t-1, \theta_{0,0})\\
&\quad + \beta_{1,1} Bel(B|A)(x-1, y-1, t, \theta_{1,1})\\
&\quad + \beta_{0,1} Bel(B|A)(x, y-1, t, \theta_{0,1})\\
&\quad + \beta_{-1,1} Bel(B|A)(x+1, y-1, t, \theta_{-1,1})\\
&\quad + \beta_{-1,0} Bel(B|A)(x+1, y, t, \theta_{-1,0})\\
&\quad + \beta_{-1,-1} Bel(B|A)(x+1, y+1, t, \theta_{-1,-1})\\
&\quad + \beta_{0,-1} Bel(B|A)(x, y+1, t, \theta_{0,-1})\\
&\quad + \beta_{1,-1} Bel(B|A)(x-1, y+1, t, \theta_{1,-1})\\
&\quad + \beta_{1,0} Bel(B|A)(x-1, y, t, \theta_{1,0}) + \beta_{0,0} Bel(B|A)(x, y, t)
\end{aligned} \tag{14}
$$

Moreover each sensor node calculates its gradient belief values from consecutive times at each time instance from equation 9, and θ can be determined from equation 10.

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.

$$
\begin{aligned}
&\psi(m_{x_i,y_j}, Bel(B|A)(x_i, y_j, t, \theta))\\
&\quad = maximum(0.5.(Bel(B|A)(x_i, y_j, t, \theta))^2 + 0.5.(m_{x_i,y_j}))
\end{aligned} \tag{15}
$$

Algorithm 1: Distributed Spatio-Temporal Algorithm

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 2: Algorithm Runs in the Central Node to Indicate the Severity of the Fire

```
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
```

$$\theta = maximum(0.5.(Bel(B|A)(x_i, y_j, t, \theta))^2 + 0.5.(m_{x_i,y_j})) \tag{16}$$

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

1) Algorithms: Spatio-Temporal Evidence Filter-Severity Vector Generation: The algorithm runs in the central node is same as the Algorithm 2. The distributed algorithm is given in Algorithm 3.

The simulation setup is similar to section F.

H. 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 Temporal Evidence Filter. Once an emergency is detected it will be switched to Spatio-Temporal Evidence Filter. The DS Belief maps generated at the central node (base station) indicate the severity level propagation of the fire with space and time.

In the second part, a severity vector generation algorithms have been introduced. Each node estimates the severity direction of the fire according to the gradient and the magnitude of the severity of the neighbouring node. Fig. 14-15 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.

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

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 the local state space computation. Based
        on its input, past knowledgebase 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
```

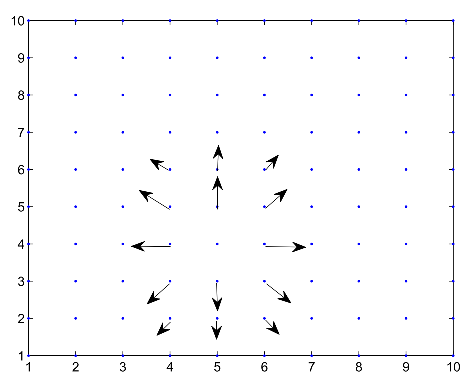

Fig. 14. Output states vectors of node, at time t = 1s.

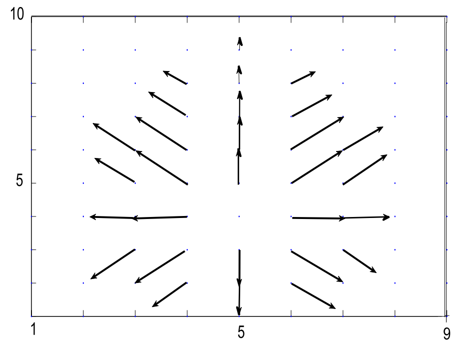

Fig. 15. Output state vectors of node, at time t = 3s.

IV. Conclusion

In this article, an information filtering framework (DS Information Filtering) for processing multi-modality sensor data has been developed. 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.

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

Practical use of the proposed concept has been studied with a simulation example of fire propagation inside a building. The output evidence signals of the corresponding filter clearly indicate the fire severity level with time at each node. Moreover, the results were compared with the Dempster-Shafer Evidence combination method, and indicate that proposed framework outperforms the existing Evidence combination method.

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 posses a global perception on the scenario. This was achieved by extending the temporal evidence filtering to Spatio-Temporal evidence filtering. Thus, each node generates a knowledgebase using the evidences gathered from sensors attached to the node and the knowledgebase of its peer nodes. This was further analyzed to produce DS belief vectors. This technique was 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. Belief maps illustrate the perception on the fire propagation in the building. The severity vector can be successfully used to build up a prediction model for emergency propagation. Moreover, different fire propagation scenarios should be investigated to further enhance the accuracy of the severity belief vector; this represents scope for future development of the framework.

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