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Dempster-Shafer Information Filtering in Multi-Modality Wireless Sensor Networks

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Abstract— A framework to estimate the state of dynamically varying environment where data are generated from heterogeneous sources possessing partial knowledge about the environment is presented. This is entirely derived within Dempster-Shafer and Evidence Filtering frameworks. The belief about the current state is expressed as belief and plausibility functions. An addition to Single Input Single Output Evidence Filter, Multiple Input Single Output Evidence Filtering approach is introduced. Variety of applications such as situational estimation of an emergency environment can be developed within the framework successfully. Fire propagation scenario is used to justify the proposed framework, simulation results are presented.

Keywords—Dempster-Shafer Belief theory, Evidence Filtering, Evidence Fusion, Sensor Modalities, Wireless Sensor Networks

I. Introduction

The emergence of Wireless sensor networks (WSNs) provide a good ground for creation of new smart sensor systems, which can be useful to further enhance 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 [1], emergency management etc. [2] [3]

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 [4], self localize [5], communicate and make decisions [6] in the deployed area.

The decisions made based on the fused information range from detecting emergency events (detect fire and the growth stage of fire), target tracking, estimating location, detecting the velocity of a dynamic object, energy consumption observation in buildings to threat detections.

However many WSNs use inexpensive sensors to compromise between cost and performance. This causes the sensor measurements to be inaccurate, and the evidence gathered may be unreliable. Especially during an emergency high uncertainty is added to the evidences due to communication link failures, sensor node failures, severe background noise etc. The use of multiple sensing modalities and fusing gathered evidences temporally and spatially can significantly enhance the robustness and the accuracy of the decision making process in such environments [7].

In WSNs prior information, conditional probability, joint probability are not known and improper initial assumptions can also weaken the integrity and the accuracy of the decision making process [8]. In this paper we use Dempster-Shafer (DS) belief theory [9], due to the advantages in DS theoretic methods specially relevant for above mentioned characteristics in WSNs. Basically DS theory does not require any prior information, conditional or joint probabilities. Moreover It has been extensively used in past decades to model imperfect, less-accurate data derived from multiple sensor modalities.

Evidence Filtering [10] is initially proposed to model imperfect data from multiple sensor modalities while making direct inferences on the frequency characteristics of events of interest, by integrating DS theory with discrete time filtering techniques. However this paper analyzes the Evidence Filtering framework in time domain to estimate the state of an dynamic environment/object. Single input single output (SISO) and multiple input single output (MISO) filtering approaches are analyzed. Moreover the framework is entirely derived within Dempster-Shafer framework. The belief about the current state is expressed as belief and plausibility functions.

A brief review of related works is provided in Section II. A brief review of Dempster-Shafer theory and Evidence filtering framework is provided in Section III. The proposed Dempster-Shafer Information Filtering is presented in Section IV. Simulation results on a fire spread scenario is presented in section V. Conclusion and future works appear in Section VI.

II. Related Work

In contrast to Dempster-Shafer theory Bayesian inference theory is widely used for the fusion of sensor information in WSNs. Kalman Filters, Monte-Carlo Filters, Particle Filters are the most popular filtering methods derived from Bayesian theory.

The work presented in [11] discusses decentralized Kalman filtering for multi modality sensor data. The research in [12] discusses distributed Kalman filtering and introduces consensus filters to track the average of multiple sensor measurements cluttered with noise. The work presented in [13] uses Bayesian filtering for localization in indoor WSNs. It mainly focuses on a new type of sequential Monte Carlo (MC) filter. Particle Filtering algorithms are efficient when modeling the complex and time varying nonlinear and non-Gaussian signal system and widely used in tracking and localization in WSNs. Some work on particle filtering are reported in [14] and [15]. The work reported in [16] compares Particle filtering algorithm and Extended Kalman filter algorithm. Eventhough the above mentioned filters are based on Bayesian theory, research presented in [17] derives Particle Filtering algorithm within DS framework.

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Demspter-Shafer Evidence Updating method presented in [18] and [6] one of the proposed methods to overcome certain drawbacks in the original DS evidence combination rule. 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. However estimation of time varying environments is not addressed in the above work.

Evidence Filtering framework reported in [10] is capable of fusing evidences to directly infer on frequency domain, which is derived from DS framework and Evidence Updating method [6]. Recursive and non recursive linear time invariant Evidence Filtering frameworks are presented in [10] [19]. However the time domain analysis is not done in the Evidence Filtering framework, as well as the noise buried in the clutter is not addressed. Our main focus is to address above two aspects.

In this paper we introduce a framework for evidence fusion which is capable of estimating time varying states, which overcomes the drawbacks associated in DS evidence combination rule. The work presented in this paper is an extension of Evidence Filtering reported in [10] where we introduce a DS evidence fusion platform with novel methods to model the input evidence signal and MISO filter.

III. PRELIMINARIES

A. Dempster-Shafer(DS) Theory

DS theory [9] can be interpreted as a generalization of Bayesian probability theory. The probabilities are assigned to sets as opposed to mutually exclusive singletons. The underline 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).

1) 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.
$m : 2^\theta \Rightarrow [0, 1]$
$m(\phi) = 0$; 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).

2) Definition 2: The upper and lower bounds of an interval is defined from the basic probability assignment (bpa).
The lower bound is referred 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 $\{\Theta, \Im, m\}, m(A) \subseteq \Theta$

$$Bel(A) = \Sigma_{B\subseteq A} m(B) \tag{1}$$

$$Pl(A) = 1 - Bel(\bar{A}) = \Sigma_{B\cap A\neq\emptyset} m(B) \tag{2}$$

3) Definition 3: Dempsters 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).

$$m(A)_\Theta = \frac{\Sigma_{C,D:C\cap D=A} m(C)_{\theta 1} m(D)_{\theta 2}}{K} \tag{3}$$

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

B. Evidence Filtering

Evidence Filtering is based on conditional belief notions [20] in DempsterShafer (DS) 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 [6] introduced to minimize the drawbacks associated in DS evidence combination rule (3).

According to evidence updating method, a knowledge base should only consider the portion of the incoming evidence that it is capable of discerning itself. Lets consider 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 $\subset \Theta$. The current knowledge base available in the first node can be updated via

$$Bel(B)_1(k + 1) = \alpha Bel(B)_1(k) + \beta Bel(B|A)_2(k) \tag{4}$$

$$Pl(B)_1(k + 1) = \alpha Pl(B)_1(k) + \beta Pl(B|A)_2(k) \tag{5}$$

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

The index k in (4), (5) denotes the temporal ordering of the evidence 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 (4) can be stated as the N^{th} order difference equation

$$Bel(B)(k) = \Sigma_{i=1}^{N} \alpha_i Bel(B)(k - i) + \Sigma_{i=1}^{N} \beta_i Bel(B|A)(k - i) \tag{6}$$

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 1.

Filter in (6) corresponds to the transfer function of the N^{th} order recursive filter.

$$H_B(z) = \frac{\Sigma_{j=1}^{N} \beta_j z^{-j}}{1 - \Sigma_{i=1}^{N} \alpha_i z^{-i}} \tag{7}$$

$Bel(B|A)(k)$ captures the incoming evidence conditioned to 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).

IV. Dempster-Shafer Information Filtering

Dempster-Shafer(DS) Information Filtering framework is introduced in this section. MISO and SISO LTI filtering techniques for information fusion are introduced and described.

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=$\{x_1, ... x_n\}$

A. 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 [6].

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

$$X_{average_{t_k}} = \Sigma_{i=1}^{N} \alpha_{i,k} X_{s_i,t_k} \tag{8}$$

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 $\Sigma_{i=1}^{N} \alpha_{i,k} = 1$; 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:

$$\zeta_{s_i,t_k} = g(X_{s_i,t_k}) \tag{9}$$

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.

$$\lambda_{t_k} = f(\zeta_{s_i,t_k}) \tag{10}$$

Where function f can be any evidence combination method, several popular methods to combine evidences are presented in [21] 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) 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 consists with one or more states x_i.

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

$$Bel(B)(t) = \Sigma_{i=1}^{N} \alpha_i Bel(B)(t-i) + \Sigma_{i=1}^{N} \beta_i Bel(B|A)(t-i) \tag{11}$$

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

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

Fig.1 represents the SISO Evidence Filter for belief functions. A similar diagram can be used to illustrate the plausibility function.

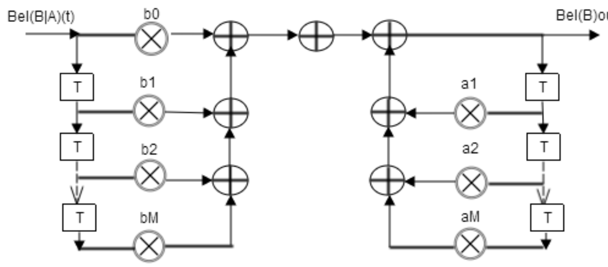

Fig. 1. Single Input Single Output Evidence Filter

B. Multiple Input Single Output Evidence Filter

Each sensor-modality generates a separate input evidence signal by obtaining evidences according to (10).

$$Bel(B)(t) = \Sigma_{k=1}^{M} \alpha_k Bel(B)(t-k) + \Sigma_{i=1,k=0}^{N,M} \beta_{s_i,k} Bel_{s_i,k}(B|A)(t-k) \tag{12}$$

$$Pl(B)(t) = \Sigma_{k=1}^{M} \alpha_k Pl(B)(t-k) + \Sigma_{i=1,k=0}^{N,M} \beta_{s_i,k} Pl_{s_i,k}(B|A)(t-k) \tag{13}$$

$$\alpha_k \geq 0; \beta_{s_i,k} \geq 0 \tag{14}$$

$$\Sigma_{k=1}^{M} \alpha_k + \Sigma_{i=1,k=0}^{N,M} \beta_{s_i,k} = 1; \tag{15}$$

The conditions in (14) and (15) are to ensure that the belief and plausibility functions constitute valid DS functions.

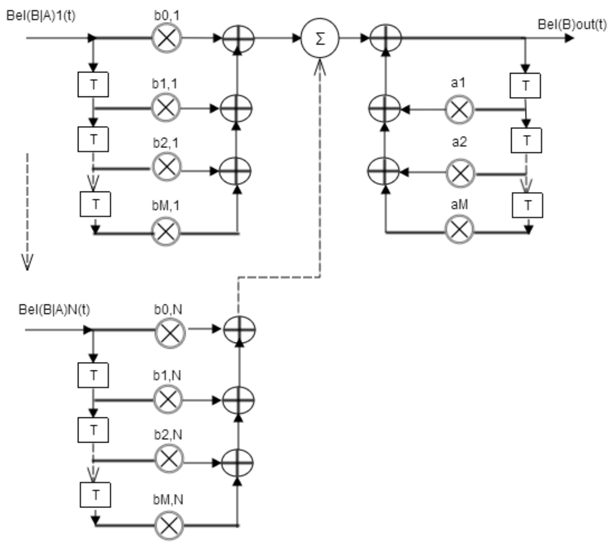

Fig. 2. Multiple Input Single Output Evidence Filter

Fig.2 represents the MISO Evidence Filter for belief functions. A similar diagram can be used to illustrate the plausibility function.

During the information filtering, 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.

V. Experimental Scenario for Fire spread model

Wireless sensor networks (WSNs) offer existing opportunities to minimize the impacts 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 in 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 directly impacts on safety of both the rescuers and victims.

A. *Simulation Setup*

Fire scenario is developed using Fire Dynamic Simulator (FDS) which is developed by National Institute of Standard and Technology (NIST), United States [22].

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 (9x4) sensor nodes. Each sensor node is attached with three sensors, to sense temperature, smoke, and optical density. At t=0, ignition starts. Ignition source is on the couch. Fig. 3 shows the simulation setup in FDS smoke view. Sampling time is set to 1s.

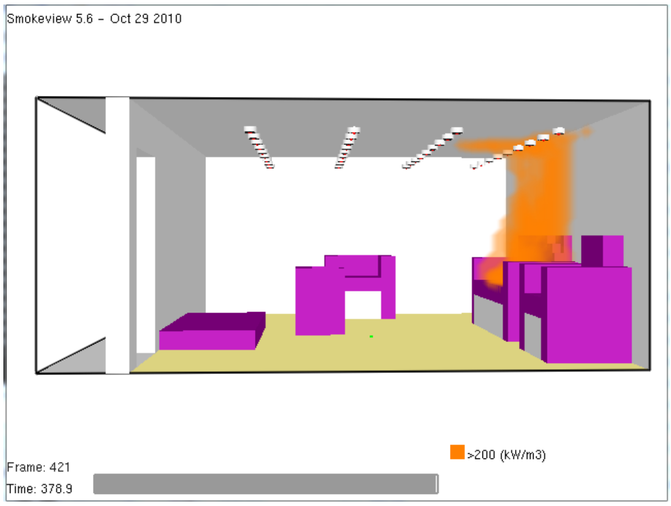

Fig. 3. Simulation setup: Living room, Sensor nodes are deployed at the ceiling

Objective of this setup is to detect emergency, and determine the growth stage of the fire or the severity level. Therefore the DS Frame of Discernment (FOD) is defined as,
DS FOD(Θ)=$\{no\ emergency, low_1, low_2.., low_n, medium_1, medium_2, ..\ medium_m, high\}$
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.

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

B. *Mass Assignment and Construction of 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.

C. Sensor Fusion

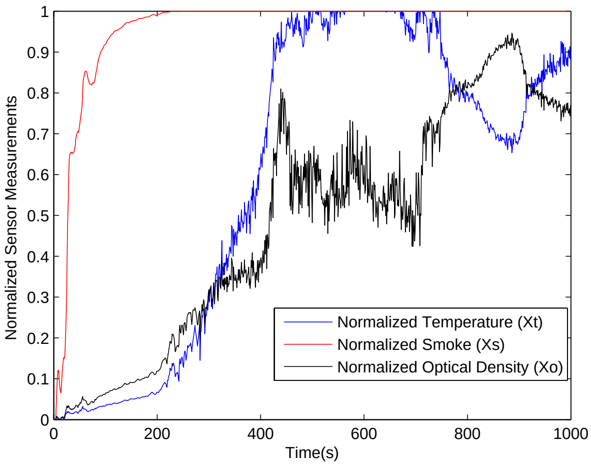

Fig. 4. Normalized Sensor Measurements at node 32 (Before Noise is Added)

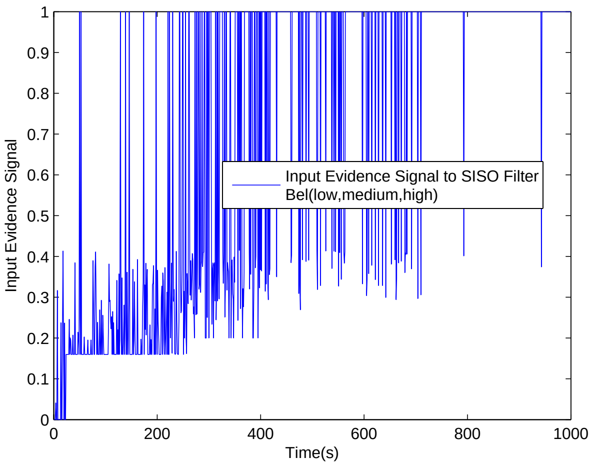

Fig. 5. Input Evidence Signal of SISO Filter-Fused Multi-Modality Evidences at node 32

1) 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.

$$Bel(B)(t) = \alpha_t Bel(B)(t-1) + \beta_t Bel(B|A)(t) \tag{16}$$

$$Pl(B)(t) = \alpha_t Pl(B)(t-1) + \beta_t Pl(B|A)(t) \tag{17}$$

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.

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

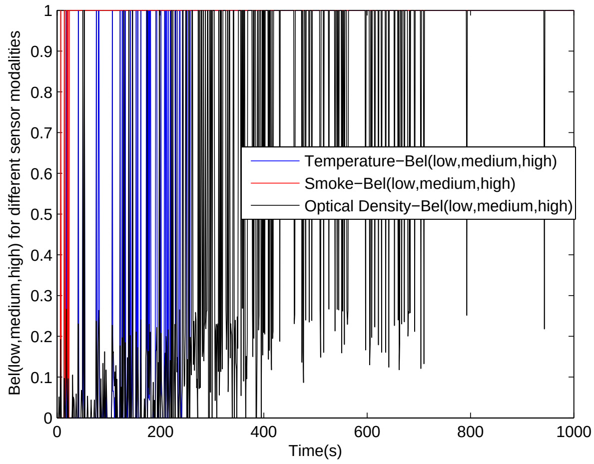

Fig. 6. Input Evidence Signals of MISO Filter at node 32

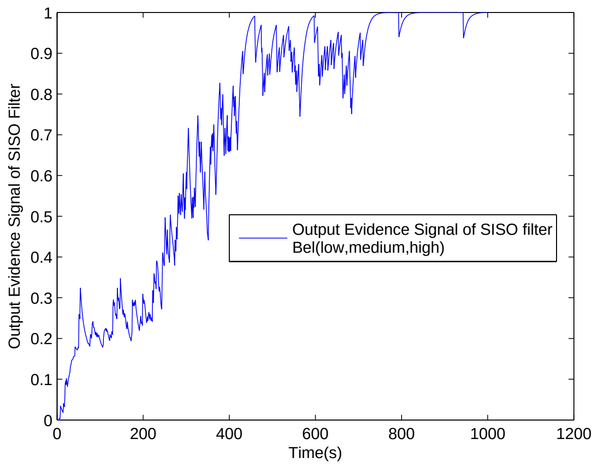

Fig. 7. Output Evidence Signal of SISO Filter at node 32

evidence signals are generated. Multiple signals are passed through first order MISO LTI Filter.

$$Bel(B)(t) = \alpha_t Bel(B)(t-1) + \Sigma_{i=1}^{n} \beta_{t,s_i} Bel_{s_i}(B|A)(t) \tag{18}$$

$$Pl(B)(t) = \alpha_t Pl(B)(t-1) + \Sigma_{i=1}^{n} \beta_{t,s_i} Pl_{s_i}(B|A)(t) \tag{19}$$

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

D. Results Analysis

Fig.4 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

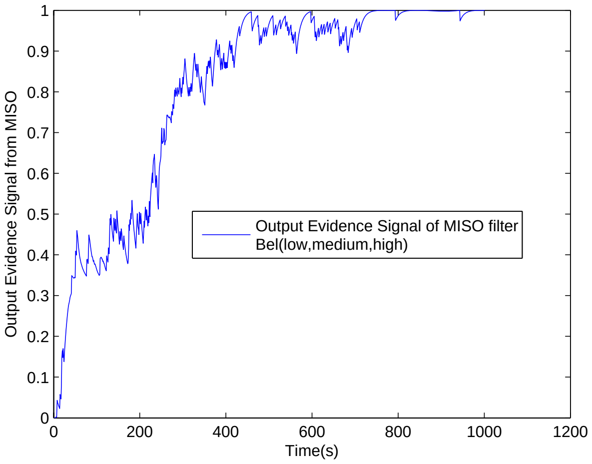

Fig. 8. Output Evidence Signal of MISO Filter at node 32

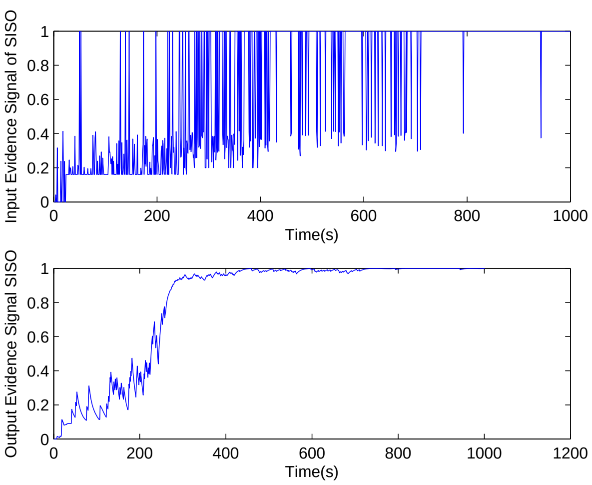

Fig. 9. Input vs Output Evidence Signals of SISO filter node 32

are implemented. Input evidence signal to SISO Evidence Filter is shown in Fig. 5. This clearly illustrates the high ambiguity in the fused results during the fire growth from low to high level. Fig. 7 shows output evidence signal from the first order SISO Evidence Filter. Output evidence signal indicates the fire scenario much clearly than the input evidence signal.

Three input evidence signals of the MISO Evidence Filter are shown in Fig. 6. These input signals are not fused until those have been sent to the filter. Ambiguity and uncertainty in the input signals are very high compare to the output evidence signal which is shown in the Fig. 8.

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. 9 and Fig. 10 compare input and output evidence signals of both filters.

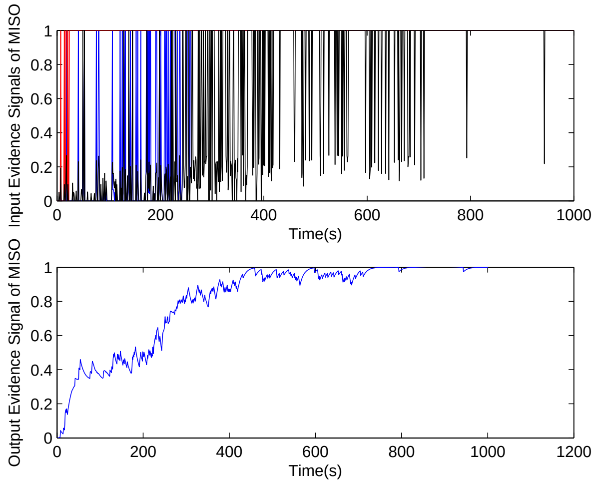

Fig. 10. Input vs Output Evidence Signals of MISO filter node 32

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. So that distributed DS Information Filtering is performed at each child node and base station node separately according to the algorithms specific to the application.

VI. Conclusion

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

Our main objective of removing noise in the clutter to minimize the uncertainty in the sensor measurements is achieved for greater extend by using both MISO and SISO Evidence Filters. The proposed DS Information Filtering framework is described with design procedures. Practical use of the proposed concept was studied with a simulation example of an indoor fire spread application.

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

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REFERENCES

[1] B.-K. Kim, S.-H. Hong, Y.-S. Jeong, and D.-S. Eom, "The study of applying sensor networks to a smart home," in *Networked Computing and Advanced Information Management, 2008. NCM '08. Fourth International Conference on*, vol. 1, pp. 676–681, 2008.

[2] C. Suh and Y.-B. Ko, "Design and implementation of intelligent home control systems based on active sensor networks," *Consumer Electronics, IEEE Transactions on*, vol. 54, no. 3, pp. 1177–1184, 2008.

[3] B. Chen and J. Wang, "Design of a multi-modal and high computation power wireless sensor node for structural health monitoring," in *Mechtronic and Embedded Systems and Applications, 2008. MESA 2008. IEEE/ASME International Conference on*, pp. 420–425, 2008.

[4] S.Gamwarige and E.C.Kulasekere, "An energy efficient distributed clustering algorithm for ad-hoc deployed wireless sensor networks in building monitoring applications," *Electronic Journal of Structural Engineering (eJSE) Special Issue: Sensor Network on Building Monitoring: from Theory to Real Application*, pp. 11–27, 2009.

[5] L. Gui, T. Val, and A. Wei, "Improving localization accuracy using selective 3-anchor dv-hop algorithm," in *Vehicular Technology Conference (VTC Fall), 2011 IEEE*, pp. 1–5, 2011.

[6] K.Premaratne, D. A. Dewasurendra, and P. H. Bauer, "Evidence combination in an environment with heterogeneous sources," *IEEE Trans.Syst.*, vol. 37, no. 3, pp. 298–309, 2007.

[7] J. L. D. L. Hall, *Handbook of Multisensor Data Fusion:Theory and Practice*. The Electrical Engineering and Applied Signal Processing Series, second ed., 2008.

[8] S. Blackman and R. Popoli, *Design and Analyis of Modern Tracking Systems*. Norwood, MA: Artech House, 1999.

[9] J. L. G. Shafer, *A Mathematical Theory of Evidence*. NJ: Princeton Univ. Press, 1976.

[10] D. Dewasurendra, P. Bauer, and K. Premaratne, "Evidence filtering," *Signal Processing, IEEE Transactions on*, vol. 55, no. 12, pp. 5796–5805, 2007.

[11] B. Rao and H. Durrant-Whyte, "Fully decentralised algorithm for multisensor kalman filtering," *Control Theory and Applications, IEE Proceedings D*, vol. 138, no. 5, pp. 413–420, 1991.

[12] R. Olfati-Saber and J. Shamma, "Consensus filters for sensor networks and distributed sensor fusion," in *Decision and Control, 2005 and 2005 European Control Conference. CDC-ECC '05. 44th IEEE Conference on*, pp. 6698–6703, 2005.

[13] A. Dhital, P. Closas, and C. Fernandez-Prades, "Bayesian filters for indoor localization using wireless sensor networks," in *Satellite Navigation Technologies and European Workshop on GNSS Signals and Signal Processing (NAVITEC), 2010 5th ESA Workshop on*, pp. 1–7, 2010.

[14] X. Sheng, Y.-H. Hu, and P. Ramanathan, "Distributed particle filter with gmm approximation for multiple targets localization and tracking in wireless sensor network," in *Information Processing in Sensor Networks, 2005. IPSN 2005. Fourth International Symposium on*, pp. 181–188, 2005.

[15] D. Hui-ying, C. Bin, and Y. Yue-ping, "Application of particle filter for target tracking in wireless sensor networks," in *Communications and Mobile Computing (CMC), 2010 International Conference on*, vol. 3, pp. 504–508, 2010.

[16] T. D. Nguyen, H. T. Trinh, V. D. Nguyen, N. T. Nguyen, T. T. Nguyen, and W. Koichiro, "A new evaluation of particle filter algorithm and apply it to the wireless sensor networks," in *Computing, Management and Telecommunications (ComManTel), 2013 International Conference on*, pp. 169–174, 2013.

[17] T. Reineking, "Particle filtering in the dempstershafer theory," *International Journal of Approximate Reasoning*, vol. 52, p. 11241135, 2011.

[18] D. E.C.Kulasekere, K.Premaratne, M.-L. Shyu, and P. H. Bauer, "Conditioning and updating evidence," *Int. J. of Approx. Reasoning*, vol. 36, no. 1, pp. 75–108, 2004.

[19] D. Dewasurendra, P. Bauer, and K. Premaratne, "Distributed evidence filtering: the recursive case," in *Circuits and Systems, 2006. ISCAS 2006. Proceedings. 2006 IEEE International Symposium on*, pp. 4 pp.–, 2006.

[20] J. H. R. Fagin, "A new approach to updating beliefs," in *Uncertainty in Artificial Intelligence, P. Bonissone, M. Henrion, L.Kanal, and J. Lemmer, Eds. New York: Elsevier*, p. 347374, 1991.

[21] K. Sentz and S. Ferson, "Combination of evidence in dempster-shafer theory," tech. rep., 2002.

[22] G. Forney, "Smokeview (Version 5), A Tool for Visualizing Fire Dynamics Simulation Data, Volume II: Technical Reference Guide," NIST Special Publication 1017-2, National Institute of Standards and Technology, Gaithersburg, Maryland, May 2009.

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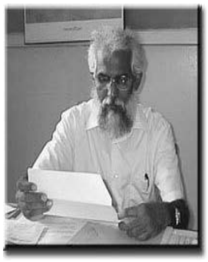

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