Detection of Forest Fire using Dezert-Smarandache Theory in Wireless Sensor Networks

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Abstract—**The most common hazard in forest is forest fire. Forest fires are as ancient as the forests themselves which destroy the forests, and can be a great threat to people who live in forests as well as wildlife. They pose a peril not only to the forest wealth but also to the entire regime utterly distressing the bio diversity, the ecology and the environment of a region. The present methods of detection of forest fire using satellite are widely considered to be scarce to foreknow the fires in the forest. Moreover, the satellite based methods of forest fire detection predict the forest fire only after the fire blowout uncontrollable and this method is considered to be futile to forecast the forest fire. Hence, a smart system is introduced which comprises of multiple classifiers to classify the forest fire attributes and fusion methods using Dezert-Smarandache theory, are considered to combine the data and to forecast the fire more accurately and effectively. The experimental results demonstrate the combined approach, which yields better accuracy in envisaging the forest fire.**

Keywords—Yager's rule; Dezert-Smarandache (DSm) theory; Support Vector Machine; Uncertainty; Forest Data Mining

I. Introduction

The forest become beleaguered with dry senescent leaves and twinges during summer, when there is no rain for months, which could spurt into flames ignited by the slightest spark [1]. The Himalayan forests, particularly, Garhwal Himalayas have been scorching regularly during the last few summers, with colossal loss of vegetation cover of that region. The youngest mountain ranges of Himalayas are the most vulnerable stretches of the world prone to forest fire. Forest fire is triggered by Natural causes as well as manmade causes [2]. High atmospheric temperatures and dryness (low humidity) offer advantageous circumstances for a fire to start. Fire is also instigated when a source of fire like naked flame, or any source of ignition emanates into contact with inflammable material. Forest fire also pose serious health hazards by producing smoke and noxious gases, as the events in Indonesia after the forest fire on the islands of Sumatra and Borneo recently have revealed the ill effects of fire [3]. The burning of vegetation gives off not only carbon dioxide but also a host of other noxious gases (Greenhouse gases) such as carbon monoxide, methane, hydrocarbons, nitric oxide and nitrous oxide, that lead to global warming and ozone layer depletion. Consequently, thousands of people grieved from grave respiratory problems due to these toxic gases. Burning forest and grasslands also augment to already serious threat of global warming. Hence, forest fire detection is very important not only to reserve the forest, but also to protect the environment.

II. Wireless Sensor Network

With the advent of the nano-age, electronic components have become expressively smaller in size and cheaper in cost. This has empowered the development of low-cost, low-power, multifunctional sensor nodes that are small in size and interconnect very fast and effectually.

The tiny sensor nodes, which entails of sensing, data processing, and communicating components, influence the idea of sensor networks based on collaborative effort of a huge number of nodes [4]. In the Fig.1, architecture of a sensor network is shown. A sensor network is self-possessed of large number of sensor nodes, which are densely organized in the forest. The position of sensor nodes need not be engineered or pre-determined. This consensus permits random deployment of sensors in inaccessible areas inside the forest.

On the other hand, this also means that sensor network protocols and algorithms must enjoy self-organizing capabilities. Another unique feature of sensor networks is the cooperative effort of sensor nodes.

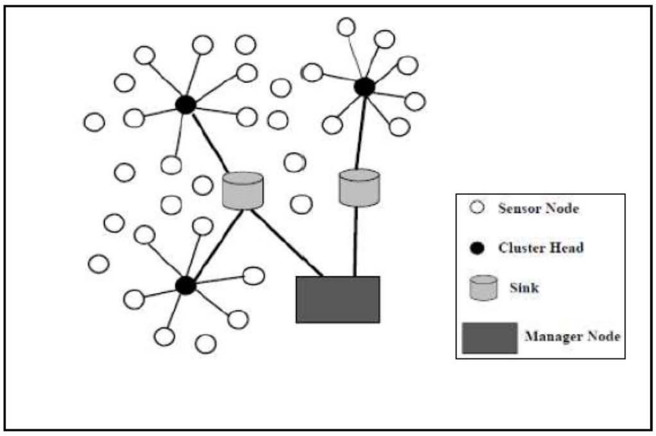

Fig. 1. Architecture of Wireless Sensor networks

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III. Related Work

It is a renowned fact that the satellite based monitoring is a prevalent technique to detect forest fire. But, the very long scan period and low resolution of satellites restrict the use and efficiency of the satellite based forest fire detection [5]. Moreover, the trouble of using satellites based method is that it cannot forecast forest fire before the fire is spread uncontrollable and occasionally the poor weather conditions (e.g. clouds) will extremely decrease the precision of satellite-based forest fire detection.

The rebellion of wireless sensor network technology in current years has made it probable to apply this technology with a possibility for early forest fire detection. Normally, the sensors used are self-organized and follow an effectual algorithm, which are combined with recent technologies.

D. M. Doolin and N. Sitar [6] system is composed of ten sensor nodes with GPS device, to sense temperature, humidity pressure and send these data back to the sink.

J. Lloret, M. Garcia, D. Bri and S. Sendra used a technology, namely, Wireless Local Area Network for the detection of fire [7]. He suggested a method of deploying a mesh network of sensors with internet protocol cameras. Fire is detected by these sensors and an alarm signal is send to the sink and an 'on' message is send to the camera in that area, which detects and provides the real image of fire. The significant role of this study is that, sensor data is combined with images. The disadvantage of the method is, it cannot forecast fire.

C. Hartung and R. Han offered a wireless system called as multi-tiered portable system for monitoring the forest fire [8]. web enabled surveillance cameras are Integrated with wireless sensor nodes, that explore the fire performance in forests. The wireless sensor network supports to deliver the status of the weather and the images are given continuously to the sink by web cameras. The main drawback of this study is that they are focused only, to determine the behavior of fire rather than the detection of fire.

B. Son [9] suggest a scheme for fire detection in South Korea using Cameras surveillance hybrid with wireless sensor networks. He suggested a clustered topology for the network. In this model, the forecast capability issues of detecting the fire are not discussed.

Hafeeda. M and Bagheri [10] presents a very smart system and embraces the probability of fire ignition and fire spread rate as well. It provides only, the moisture content in the trees of forest.

Yu and Wang designed a model which applies neural network methodology for in-network data processing in environmental sensing applications of WSN [11]. Data is propagated to the sink in the wireless sensor network. The drawback of this system is that, it is not focused on temperature.

Ngai, Zhou, Lyu and Liu projected a universal reliability-centric framework for event reporting in WSNs which is also applicable to forest fire detection systems [12]. They considered the accuracy, importance and freshness of the reported data in environmental event detection systems. In this system, the forecasting of fire is not deliberated.

Then, neural network based single classifier using wireless sensor network is used to classify the data of Fire or No Fire [13]. Here, the processing of data is through a single classifier. Instead of relying on a single classifier, it is proposed a smart and robust system for forest fire detection which has multiple classifiers.

IV. Working of Classifiers

The foremost goal of classifiers is to classify the data into their respective classes of Fire or Intermediate Fire or No Fire. The better the classification accomplished the healthier the possibility of detecting and forecasting the forest fire. Multiple classifiers are used in a system in order to make the system more reliable leading to an advantage of overcoming the weaknesses exhibited by any classifier. Recently, Support Vector Machine (SVM) has been documented as a better tool to deal with high-dimensionality data like in the case of forest as it involves thousands of acres [14].

The main aim of support vector machines is to find hyper-planes that separate data points into their respective classes of Fire or Intermediate Fire or No Fire. Possibility of data classification is attained when the separation between classes is appropriately identified. In order to determine the equation of the hyper-plane, the support vector machine hunts for those data points that lie closer to data points of another class. These points are called "support vectors". The number of input vectors defines the dimension of the input space [15]. If there are two linearly separable classes of data, the goal is to find a line that separates the two classes from each other, thereby establishing the input values that define the two classes.

Support vector machine solves ranking problems. In support vector machine, linear separating hyper-plane with a maximum-margin in the higher feature space is induced by the kernel function. Some common kernel functions include polynomial, RBF, sigmoid, etc. After substituting the approximate RBF kernel into the classification formula, it is possible to classify the data into the classes of Fire or Intermediate Fire or No Fire. The combination of classified outputs from the classifiers is accomplished by fusion theory.

V. Preliminary Work

The most valuable combination rule is a class of unbiased operators developed by Ron Yager. Yager's fusion engine is used to combine the data from the classifiers. Yager views out that a noteworthy feature of combination rules is the ability to update an already combined structure when new evidence becomes available. This is generally denoted as updating and the algebraic property that facilitates this, is associativity. The meaning of quasi-associativity is that, the operator can be broken down into associative sub-operations [16]. With the help of the notion of quasi-associative operator, Yager advances a general framework to look at combination rules where associative operators are a proper subset.

To report the matter of conflict, Yager starts with a vital difference between the basic probability mass assignment (m) and the ground probability mass assignment (q). The main variances between the basic probability assignment and the ground probability assignment are in the normalization factor and the mass attributed to the universal set. The combined ground probability assignment is defined in the equation below.

$$q(C) = \sum_{A \cup B = C} m_1(A)\, m_2(B) \tag{1}$$

Where, C is the union of subsets A and B [both in the power set P (X)], and q(C) means the ground probability assignment associated with C, recognized as yager's combination rule. Though the yager rule of combination is not associative, the combined structure q(C) can be used to comprise any number of pieces of evidence. Through the quasi-associativity that yager describes, the combined structure q(C) can be reorganized based on new evidence.

This is achieved by merging the ground probability assignment associated with the new evidence and the ground probability assignment of the already existing combination through the above formulae and then converting the ground probability assignments to basic probability assignments. As formerly mentioned, one apparent discrepancy between combination with the basic and the ground probability assignment functions is the absence of the normalization factor (1-K).

In yager's formulation, normalization is avoided by permitting the ground probability mass assignment of the null set to be greater than 0,

$$q(\Phi) \geq 0 \tag{2}$$

q(Φ) is calculated in precisely in the same manner of other combination rules [10]. But, yager adds the value of the conflict denoted by q(Φ) to the ground probability assignment of the universal set, q(X), to produce the conversion of the ground probabilities to the basic probability assignment of the universal set $m^Y(X)$:

$$m^Y(X) = q(\Phi) + q(X) \tag{3}$$

Therefore, instead of normalizing out the conflict, yager ultimately attributes conflict to the universal set X through the conversion of the ground probability assignment to the basic probability assignments. The interpretation of the mass of the universal set (X) is the degree of ignorance.

The elementary algebraic properties that this rule satisfies are commutativity and quasi associativity, but not idempotence or continuity. The ground probability assignment functions (q) for the null set, Φ, and an arbitrary set A, are transformed to the basic probability assignment function associated with this yager's rule (m^Y) by:

$$m^Y(\Phi) = 0 \tag{4}$$

$$m^Y(A) = q(A) \tag{5}$$

The basic probability assignments related with yager's rule (m^Y) are not same as with other combination rules (m) [17]. But, yager offers the relationship with other rules as detailed below.

$$m(\Phi) = 0 \tag{6}$$

$$m(X) = q(X) / 1\text{-}q(\Phi) \tag{7}$$

$$m(A) = q(A) / 1\text{-}q(\Phi) \tag{8}$$

$$\text{for } A \neq \Phi, X$$

VI. Problem Statement and Proposed Work

The supervision of continuous and large data is an issue of main interest in forest fire detection. The sensors multiplicity in forest fire detection makes the decision-making procedure more multifaceted. Thus, it is very problematic to find the reliable information in such information mass.

The core problem is to make a decision when two or more experts give inconsistent information. Henceforth, it is obligatory for executing a true fusion engine for localization information; with a principle of conditioning and for this case, the Dezert-Smarandache rule seems to be very effective. Current advances in Dezert-Smarandache theory have revealed that this theory was able to handle the flaw between proposals in a quite elastic way. Dezert-Smarandache rule is used as fusion engine in our forest fire detection.

Besides, when indications are highly conflicting, fusion result will be inappropriate and tiny changes of basic probability assignment function in this rule can bring shrill changes of fusion result. Moreover, if there are disaccords between one piece of evidence and several other evidences, ridiculous result will be made. Hence, it is essential to implement the Dezert-Smarandache theory. Fig. 2 shows the architecture of proposed work in the forest fire detection using Dezert-Smarandache theory. The proposed smart and robust system for forest fire detection consists of three different classifiers for classifying the large forest data. Processing of data such as temperature and humidity are via classifiers.

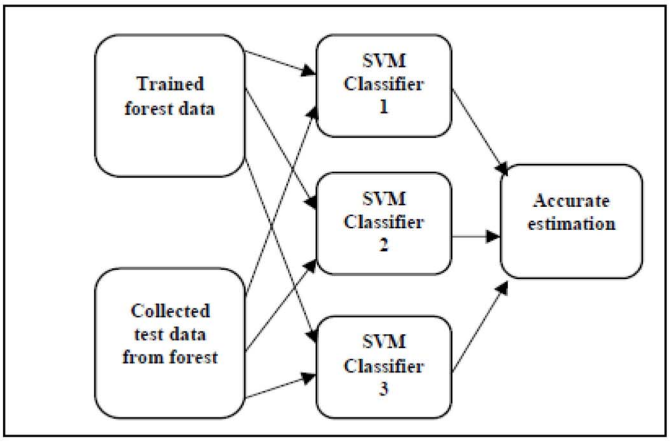

Fig. 2. Architecture of the Smart System

The forest fire attributes such as temperature, humidity measured periodically by the sensor nodes, are sent to the smart system. The intellectual system which comprises of three different classifiers such as SVM, SVMRBF Sigma=0.3 and SVMRBF Sigma=0.9999 (SVM Radial Basis Function) denoted as 1, 2 and 3 in the architecture shown above, process the data. Each of the above said classifiers deliver the theories for each class such as No Fire, Intermediate Fire and Fire.

These pieces of evidence are then combined to reach a final decision using Dezert-Smarandache combination formula. The experiments are accomplished on forest data such as temperature and humidity.

The method projected above has two primary advantages. One advantage is that robustness across multiple datasets with multiple classifiers. Suppose if it is a single classifier and the classifier misclassifies, in the important event like forest fire, the cost is too high. Hence, instead of trusting on a single classifier, multiple classifiers are introduced. While doing so, the grouping of classifiers overwhelms the weaknesses showed by anyone classifier to a particular data set and helps to perceive the forest fire more precisely by curtailing the problem of training and testing under conditions of large, inadequate and noisy data. The second one, management of uncertainty in the presence of unequal error costs. In this forest fire context, it is a good practice to consider temperature and humidity because very high temperature and low humidity are the vital aspects for forest fire.

VII. Dezert-Smarandache Theory

The Dezert-Smarandache theory (DSmT) of reasonable and inconsistent reasoning proposed by the authors in recent years can be measured as an extension of the classical Dempster-Shafer theory (DST) but includes essential changes with the DST [18].

Dezert-Smarandache theory allows to properly combine any types of independent sources of information represented in terms of belief function, but is mainly focused on the fusion of uncertainty, highly contradictory and vague sources of evidence. Dezert-Smarandache theory is able to solve complex static or dynamic fusion problems beyond the limits of the DST framework, especially when conflicts between sources become large and when the modification of the frame of the problem under consideration, denoted Θ, becomes unapproachable because of the vague, relative and imprecise nature of elements of Θ. The basis of DSmT is based on the definition of the Dedekind's lattice D^{Θ} also called hyperpower set of the frame Θ in the result.

In the DSmT framework, Θ is first considered as only a set $\{\theta_1, \ldots, \theta_n\}$ of n exhaustive elements without introducing other constraint. The exhaustivity hypothesis is not essential actually, because one can always close any open world theoretically, Θ by including into it an extra element / hypothesis θ_0 corresponding to all missing hypotheses of Θ to work with the new closed frame $\Theta = \{\theta_0\} \cup \Theta = \{\theta_0, \theta_1, \ldots, \theta_n\}$. The proper use of the free DSm model for the fusion depends on the inherent nature of elements (e.g. the relative concepts of fire/no fire, smallness/tallness, pleasure/pain, hot/cold, etc.), In such case, we just call Θ the frame of the problem.

When a complete refinement of Θ is possible and thus allows us to work on Θ, then we call Θ the frame of discernment of the problem because some elements of Θ are truly exclusive and thus they become visible. The refined frame of discrimination assuming exclusivity of all elements $\theta i \in \Theta$ agrees to the Shafer's model and can be attained from the free DSm model by presenting into its all individuality constraints. All fusion glitches dealing with truly exclusive concepts must deceptively be based on such model since it defines sufficiently the factual and basic nature of hypotheses. Actually, any constrained model, including Shafer's model, agrees to what we called a hybrid DSm model. DSmT provides a widespread hybrid DSm rule of combination for working with any kind of hybrid models including exclusivity and non-existential constraints as well and it is not only limited to the most constrained one model. The formula for the mass functions of a combination is given as

$$m(C) = \sum_{\substack{A,B \in D^{\Theta} \\ A \cap B = C}} m_1(A)\, m_2(B) \qquad (9)$$

Since D^{Θ} is closed under $\cup$ and $\cap$ set operators, this new rule of combination guarantees that m(.) is a proper generalized belief assignment, i.e. $m(.) : D^{\Theta} \rightarrow [0, 1]$. This rule of combination is commutative and associative and can always be used for the fusion of sources involving fuzzy concepts.

VIII. Proposed Algorithm

Let $\Theta = \{\theta_F, \theta_{IF}, \theta_{NF}\}$ be a frame of discernment. The masses m(A), m(B) and m(C) are the basic belief assignments of three sources which are independent with each other, where

$$\sum_{A \in D^{\Theta}} m_1(A) = 1 \text{ and } \sum_{B \in D^{\Theta}} m_2(B) = 1.$$

Step 1:

Compute $m_1(A)$ and $m_2(B)$ using the formula number of sensors broadcasting as F, IF and NF divided by total number of sensors deployed.

Step 2:

Calculate the mass of F, IF and NF using the formula,

$$m_{ij}(F) = \sum_{\substack{i,j=1 to 3 \\ i,j \in D^{\Theta}}} m_i(F) m_j(F)$$

$$m_{ij}(IF) = \sum_{\substack{i,j=1 to 3 \\ i,j \in D^{\Theta}}} m_i(IF)\, m_j(IF)$$

$$m_{ij}(NF) = \sum_{\substack{i,j=1 to 3 \\ i,j \in D^{\Theta}}} m_i(NF)\, m_j(NF)$$

The total masses of the elements from one classifier are equal to 1 and the same principle is applied for the remaining classifiers.

Step 3:

If all classes such as F, IF and NF have been computed then go to step 4, otherwise go to step 2.

Step 4:

Compute belief function of F, IF and NF using the formula,

$$Bel(F) = \sum_{\substack{k=1 to 3 \\ k \in D^{\Theta}}} m_k(F)$$

$$Bel(IF) = \sum_{\substack{k=1to3 \\ k \in D^{\Theta}}} m_k(IF)$$

$$Bel(NF) = \sum_{\substack{k=1to3 \\ k \in D^{\Theta}}} m_k(NF)$$

Step 5:

$\forall X \in D^{\Theta}$, $X \neq \emptyset$, from the calculated belief, the highest value shows the decision of the engine, whether it is Fire or Intermediate Fire or No Fire. Here, m(X) is used to denote the fusion result.

IX. COMPARITIVE ANALYSIS AND RESULTS

The data sets which were used in this analysis are the inert data collected from the forest department [19]. A sample of 151 data are used and the test results using MATLAB were carried out on forest data containing temperature and humidity collected by sensor nodes. The sample data having three classes namely Fire, Intermediate Fire and No Fire and four attributes namely Low Humidity, High Humidity, Low Temperature, High Temperature are taken as training set for the purpose of classification.

The masses from the engine output data of forest fire for the three classifiers namely, Support Vector Machine denoted by SVM, SVMRBF (Sigma=0.3), SVMRBF (Sigma=0.9999) are given in the TABLE I. The combination precision is high compared to individual classifier. This type of combination may predominate the complications of false detection and is found to be precise. According to the results taken the masses are tabulated in the following TABLE I.

TABLE I. OUTPUT FROM THE CLASSIFIERS

Classifiers	Fire	Intermediate Fire	No Fire
SVM Polynomial	0.2781	0.2848	0.0596
SVM RBF ($\sigma = 0.3$)	0.245	0.3245	0.0132
SVM RBF (σ=0.9999)	0.3245	0.2185	0.0663

From the TABLE I, fusion of three classifiers using the yager's rule of combination was deliberated. The value of mass for Fire, Intermediate Fire and No Fire is calculated. There is no normalizing factor, K as in the case of dempster's theory. The calculation gives a counter-intuitive result, when combining the data from the three classifiers using the yager's rule of combination. Whereas, if one applies the DSmT rule, it affords a reliable and judicious solution to the combination of conflict resources.

The yager rule provides the combination and the mass of belief function is calculated to be as m(F)=0.3667, m(IF)=0.3156, m(NF) = 0.1823, m(F U IF) = 0.0196, m(FUNF) = 0.0706, m(IF U NF) = 0.0432, m(FUIFUNF)=0.0019. The belief of F, IF and NF are calculated as Bel(F) = 0.4570, Bel(IF) = 0.3785 and Bel(NF)=0.2961. The highest value of belief is taken as the decision of yager engine [20].

The DSmT rule of combination provides as m(F)=0.1400, m(IF) = 0.0885, m(NF) = 0.0156, m(F U IF) = 0.0002, m(FUNF) = 0.0106, m(IF U NF) = 0.0025, m(FUIFUNF)=2.2994, m(F∩IF) =0.2711, m(F∩NF) = 0.0409, m(IF ∩ NF) = 0.0426, m(F ∩ (IF U NF)) = 0.1014, m(IF∩(FUNF)) = 0.1814, m(NF ∩ (F U IF)) = 0.0047, m(FU(IF ∩ NF)) = 0.0203, m(IFU(F∩NF)) = 0.0120, m(NFU(F∩IF))=0.0675.

The belief of F, IF and NF are calculated as Bel(F)=0.8505, Bel(IF) = 0.7927, and Bel(NF) = 0.5000. The belief masses are converted into the number of sensor for the two engines and the same is plotted in Fig. 3.

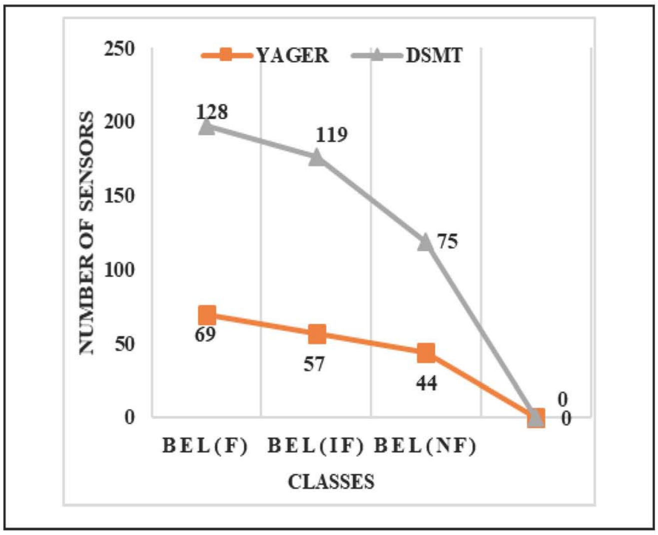

Fig. 3. Beliefs of Yager and DSmT

The beliefs of Fire, Intermediate Fire and No Fire of DSmT engine and Yager engine considering the number of sensors is plotted in Fig. 3. It is concluded from the Fig. 3, that the belief of DSmT is more than that of Yager engine, which endorses a higher reliability on the part of DSmT engine than Yager engine. The highest value of belief is taken as the decision of DSmT rule.

The accuracy for Yager and DSmT is calculated as shown in the TABLE II.

TABLE II. ACCURACY IN PERCENTAGE (%)

Engines	Fire	Intermediate Fire	No Fire
Yager (Olivier,Steven,Bart) [20]	45	37	29
DSmT (Proposed work)	85	79	50

From the TABLE II, the accuracy of DSmT is more than yager's rule. The DSmT rule embraces good for the above example. The DSmT rule suggests a new model for solving the above controversy by working directly on hyper power set. In this DSmT model appropriate mass transfer of all the sources of conflicts are accomplished.

The comparison of accuracies of Yager and DSmT is plotted in Fig. 4.

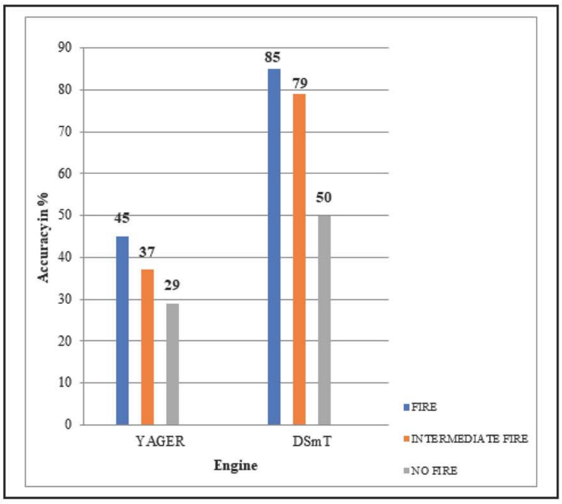

Fig. 4. Comparison of accuracies of Yager and DSmT

Fig. 4 illustrates that, the accuracies of DSmT engine are higher than that of Yager engine for the same data set.

X. CONCLUSION

DSmT has to be observed as a general flexible bottom-up approach for handling uncertainty and conflicts for an extensive class of static or dynamic fusion problems where the information to combine is modelled as a finite set of belief functions provided by different independent sources of evidence in this forest fire context. The growth of DSmT emerged from the fact that the conflict between the sources of evidence arises from the unreliability of sources themselves.

This sample was scrutinized and the results of yager's rule are examined which validates the high degree of conflict arising, showing the weakness of the yager rule. The accuracies of yager rule for above sample are only 45% for fire, 37% for intermediate fire and 29% for no fire. This is one of the major drawback of yager theory. Whereas, the accuracies of DSmT rule shows 85% for fire, 79% for intermediate fire and 50% for no fire. It is concluded that, DSmT is more reliable than yager rule even for the small dataset.

The DSmT framework can easily handle not only exclusivity constraints, but also non-existential constraints or mixed constraints as well which is very useful in some dynamic fusion problems. DSmT allows to work at any level of modelling for handling uncertainty and conflicts, depending on the fundamental nature of the problem. This ability of DSmT allows to deal formally with any fusion problems articulated in terms of belief functions which can blend discrete concepts with vague/continuous/relative concepts.

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