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ASSESSMENT OF PROPORTIONAL CONFLICT REDISTRIBUTION RULES FOR FOREST FIRE DETECTION

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Abstract- In this paper, three versions of Proportional Conflict Redistribution rule (PCR) for information fusion in the context of forest fire detection is proposed. From PCR1 to PCR3, one increases the intricacy of the rules and also the literalness of the restructuring of conflicting masses. The PCR rules redistribute the conflicting mass, after the conjunctive rule has been applied, proportionally with some functions depending on the masses assigned to their corresponding columns in the mass matrix. Out of these three PCR rules, one rule can be chosen depending on the complexity one wants to deal with in the application of forest fire detection and their fusion systems. PCR3 rule outperforms in terms of efficiency than other two PCR rules. Further, it is observed that the accuracy of PCR3 ruins the same for both the cases of failure and without failure of node / link.
Keywords – Dempster's rule, Yager's rule, Dezert-Smarandache theory (DSmT), Data fusion, Belief function, Proportional Conflict Redistribution (PCR) rules.

1. INTRODUCTION

Forests are the shields of earth's ecological balance. Forest fire is generally detected when it has already spread over a large extent, making its control and stoppage difficult and even impossible at times. Apart from instigating disastrous loss of lives and valuable natural and individual properties including thousands of hectares of forest and hundreds of houses, forest fires are a great peril to naturally grown forests and fortification of the environment [1]. The problem with forest fires is that the forests are usually remote and millions of hectares of forest are ruined by fire every year. The fire detonation may be caused through human actions like smoking or camp fire or by natural reasons such as high temperature in a hot summer day thus leading to fire ignition. There are a number of detection and monitoring systems in the form of patrols or monitoring towers, aerial and satellite monitoring [2] and progressively endorsed detection and monitoring systems based on optical camera sensors, and different types of detection sensors or their combination.

The rest of the paper is organized as follows. Wireless sensor networks are explained in section II. Failure in wireless sensor networks are elucidated in section III. Literature Survey is detailed in section IV. Brief review of fusion rules is presented in section V. Proportional Conflict Redistribution is detailed in section VI. Experimental Results and Analysis are narrated in section VII. Concluding remarks are summarized in section VIII.

2. WIRELESS SENSOR NETWORKS

In Wireless sensor network technologies usually deploy a large number of small, low cost sensors, fairly densely that can witness and influence the physical world around them by gathering physical data, alter it into electrical signals, send it to a remote location to do some study and organize the results in forest fire application [3]. There is no prerequisite to build towers or set up intricate communication links such as; microwave and satellite. It can be deployed anywhere, even in unapproachable places. This technology can afford a real time monitoring for forest fire, where it can provide information at the ignition instance or at very small delay, depends on the node used wake up / sleep schedule. It's more unswerving because it can impact the world in the surrounded area, if it is used in relevant means, rather than expecting events over large distances and long delay like other satellite and camera towers techniques [4]. In this work, all nodes only use temperature and humidity sensors and they are programmed on a certain threshold temperature, above it the node will send an alarm message to the sink. This concept relies solely on the node behavior to alert of crises possibility using simple node components to deliver detection and information on whether this is a peaceful fire, or the beginning of wild fire. The key in this method is to make decisions by tracking the fire proliferation and check the logic behind it.

3. FAILURE IN WIRELESS SENSOR NETWORKS

Forest fire detection is one of the utmost safety-critical application. Failures are unavoidable in Wireless Sensor Networks due to the lack of monitoring and unattended deployment. There are many issues related to energy, memory and computational

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ability of a sensor node. The occurrences of faults are mostly due the presence of faulty sensor nodes [5]. In certain situations, sensor node may give incorrect data due to some faults in it. Failed nodes may decrease the quality of service (QoS) of the entire WSN. In case of node failure, a connection between some sensors and the sink might be lost and that could leave a gap in the network coverage, hence loss in the forest data occurs. WSN node faults are usually due to the following causes: the failure of modules (such as communication and sensing module) due to fabrication process problems, environmental factors, enemy attacks and so on; battery power depletion; being out of the communication range of the entire network [6]. Since the network is unaware of the fault, it might lead to a serious problem. So, our objective is to detect the occurrence of fire in the forest, though there is failure in link or nodes as well as the probability of fire to reduce the disastrous loss.

4. LITERATURE SURVEY

There are several concerns in forest fire detection, of which the most significant ones are about different sensor combinations and suitable methods for quick and noise-tolerant fire detection. Researchers have been studying fires taking place in various places such as residential area [7], forest and mines [8] to find some results for fire monitoring. Several decades of forestry research have resulted in many advances in field of forest fire monitoring. The Fire Weather Index (FWI) system being established by the Canadian Forest Service and the National Fire Danger Rating System (NFDRS) introduced by the National Oceanic and Atmospheric Administration [9] are two examples of such advances. Lu Zhiping et al. [10] anticipated a forest fire detection solution using wireless sensor networks. Their system is made of sensor nodes, gateways, and task managers. Each sensor node is equipped with temperature and humidity sensors. After procurement of sensory information at sensor nodes, data are merged at gateways and data-analysis and decision making are done by task manager nodes. Bagheri [11] applied FWI index and his inventive k-coverage algorithm to detect forest fires. This algorithm monitors each point by using k or more sensor nodes to increase fault tolerance and therefore, some sensors can be put in standby mode to outspread network lifetime. Though there are various algorithms to find the minimum number of sensors to be used, they are usually NP complete problems [12]. The proposed k-coverage solution proved to extend the network life time. Forest fire detection was not the emphasis of this work and was considered as an application for the novel k-coverage problem.

A skyline approach for early forest fire detection is proposed [13]. Skyline is built using greater values, i.e., those sensor readings with large temperature and high wind speed. But, only data on skyline are sent to a sink to be used for fire detection and sink processes the data according to the recommended algorithm and results in a fast and energy efficient forest fire detection. Fire detection method using k-nearest neighbor's algorithm (K-NN) is projected [14] and it is a technique for unifying objects based on closest training data in the feature space. K-nearest neighbor algorithm is amongst the modest of all machine learning algorithms and it is an instance-based learning algorithm for forest fire detection. But the precision of the k-NN algorithm can be severely degraded due to the noise from the environment or irrelevant features. A real time forest detection scheme [15] was predicted based on neural network classifiers, where, the distributed processing scheme, with data processing at cluster heads, and imperative data gets associated and collected at the central station for eventual decision making. Under the real time detection environments, the system is multifaceted to interpret and needs healthier tactics for data processing, communication and collection for final decision.

5. BRIEF REVIEW OF FUSION RULES

An extensive diversity of combination rules exists and an assessment and classification are proposed, where the rules are scrutinized according to their algebraic properties as well as on different examples [16]. A current study of main fusion rules can also be found in [17, 18]. To abridge the notations, consider only two independent sources of evidence E_1 and E_2 over the same frame Θ with their corresponding Basic Belief Assignments (BBA) $m_1(.)$ and $m_2(.)$. Most of the fusion operators proposed in the literature so far use either the conjunctive operator, the disjunctive operator or a specific combination of them. These operators are respectively defined ∀A ∈ G, by

$$m_\wedge(A) = (m_1 \wedge m_2)(A) = \sum_{\substack{X,Y \in G \\ X \cap Y = A}} m_1(X) m_2(Y) \tag{1}$$

$$m_\vee(A) = (m_1 \vee m_2)(A) = \sum_{\substack{X,Y \in G \\ X \cup Y = A}} m_1(X) m_2(Y) \tag{2}$$

The degree of conflict between the sources E_1 and E_2 is defined by

$$k_{12} \triangleq m_\wedge^{12}(\emptyset) = \sum_{\substack{X,Y \in G \\ X \cap Y = \phi}} m_1(X) m_2(Y) \tag{3}$$

If k_{12} is close to 0, the basic belief assignments $m_1(.)$ and $m_2(.)$ are nearly not in conflict, while if k_{12} is close to 1, the basic belief assignments are almost in total conflict. Next, we briefly review the foremost common fusion rules encountered in the literature and used in engineering applications.

5.1 Dempster's rule –

This combination rule has been anticipated by Dempster [19]. The sources of evidence are equally consistent, otherwise a discounting preprocessing is first applied. It is defined on $G = 2^\Theta$ by forcing $m_{DS}(\emptyset) \triangleq 0$ and $\forall A \in G^*$ by

$$m_{DS}(A) = \frac{1}{1-k_{12}}\, m_\wedge(A) = \frac{m_\wedge(A)}{1-m_\wedge(\emptyset)} \tag{4}$$

when $k_{12} = 1$, this rule cannot be used. Dempster's rule of combination can be directly prolonged for the combination of, N independent and equally unswerving sources of evidence and its main interest comes essentially from its commutativity and associativity properties [20]. Dempster's rule corresponds to the normalized conjunctive rule by uniformly reassigning the mass of total conflict onto all focal elements through the conjunctive operator. The non-normalized version of the Dempster's rule corresponds to the Smet's fusion rule in the TBM (Transferable Belief Model) framework working under an open world assumption,

i.e. $m_S(\emptyset) = k_{12}$ and $\forall A \in G^*, m_S(A) = m_\wedge(A)$. (5)

5.2 Yager's rule –

Yager confesses that in case of conflict, Dempster's rule provides counter-intuitive results [21]. Thus, k_{12} plays the role of an absolute discounting term added to the weight of ignorance. The commutative and quasi-associative rule is defined by Yager and Yager's rule is given for $m_Y(\emptyset) = 0$ and $\forall A \in G^*$ by

$$m_Y(A) = m_\wedge(A) \tag{6}$$

$$m_Y(\Theta) = m_\wedge(\Theta) + m_\wedge(\emptyset) \tag{7}$$

5.3 Dezert-Smarandache Theory (DSmT) –

Proposed by Jean Dezert [22], and within the DSmT framework and when the free DSm model $M^f(\Theta)$ holds, the conjunctive consensus, called the DSm rule, is performed on $G = D^\Theta$. DSm rule of two independent sources correlated with $m_1(.)$ and $m_2(.)$ is thus given by

$$m_{DSm}(A) = \sum_{\substack{X,Y \in G \\ X \cap Y = A \\ X \cup Y = A}} m_1(X) m_2(Y) \tag{8}$$

Since G is closed under ∪ and ∩ set operators, DSm rule guarantees that m(.) is a proper belief assignment, i.e. m(.): G→ [0, 1]. DSm rule is commutative, associative and can always be used for the fusion of sources involving fuzzy concepts whenever the free DSm model holds. This rule is directly and easily extended for the combination of $s > 2$ independent sources.

6. PROPORTIONAL CONFLICT REDISTRIBUTION RULE (PCR)

6.1 Principle of PCR rule –

As an alternative of applying a direct transfer of partial conflicts onto partial uncertainties as with DSm rule, the idea behind the Proportional Conflict Redistribution (PCR) rule [23] is to transfer conflicting masses (total or partial) proportionally to non-empty sets involved in the model according to all integrity constraints. The general principle of PCR rule is given as,

1. Calculate the conjunctive rule of the belief masses of sources;
2. Calculate the total or partial conflicting masses
3. Redistribute the conflicting mass (total or partial) proportionally on non-empty sets involved in the model according to all integrity constraints.

The way the conflicting mass is redistributed yields essentially to three forms of PCR rules, denoted as PCR1, PCR2, PCR3 which have been presented in [24]. These PCR fusion rules toil for any degree of conflict $k_{12} \in [0, 1]$ or $k_{12\ldots s} \in [0,1]$, for DSm models and both in DST and DSmT frameworks for static or dynamical fusion problematics. The PCR rule reorganizes the partial conflicting mass to the elements involved in the partial conflict, considering the conjunctive normal form of the partial conflict. PCR is the most mathematically exact redistribution of the conflicting mass attained after the conjunctive rule. PCR rule preserves the neutral impact of the vacuous belief assignment because the mass of the focal element Θ cannot be involved in the conflict. Since Θ is a neutral element for the intersection (conflict), Θ gets no mass after the redistribution of the conflicting mass. We present below only the most sophisticated proportional conflict redistribution rule, since this rule is what we sense the most effectual PCR fusion rule developed for detection of fire in the forest.

6.2 Proportional Conflict Redistribution rule1 –

It is unconventionally industrialized a Proportional Conflict Redistribution Rule (PCR1) [25], which harmoniously involves in two steps. First, applying the conjunctive rule to the basic belief assignments $m_1(\cdot)$ and $m_2(\cdot)$. Second, redistribute the total conflicting mass k_{12} to all nonempty sets in S^Θ proportionally with their nonzero mass sum, i.e. for the set, say Fire in the context of forest fire detection, proportionally with the weighting factor:

$$w_{SD}(Fire, m_1, m_2) = m_1(Fire) + m_2(Fire) \neq 0 \tag{9}$$

The analytical formula for PCR1, non-degenerate and degenerate cases, is:

$$m_{PCR1}(\emptyset) = 0, \tag{10}$$

and $\forall Fire \in S^\Theta \setminus \emptyset$,

one has $$m_{PCR1}(Fire) = \sum_{\substack{X_1, X_2 \in S^\Theta \\ X_1 \cap X_2 = Fire}} m_1(X_1) m_2(X_2) + c_{12}(Fire) \frac{c_{12}(Fire)}{d_{12}} . k_{12} \tag{11}$$

where

$c_{12}(Fire)$ is the sum of masses corresponding to set Fire,

i.e. $c_{12}(Fire) = m_1(Fire) + m_2(Fire) \neq 0$,

d_{12} is the sum of nonzero masses of all nonempty sets in S^Θ assigned by the sources $m_1(.)$ and $m_2(.)$

(in many cases $d_{12} = 2$, but in degenerate cases it can be less),

k_{12} is the total conflicting mass.

6.3 Proportional Conflict Redistribution rule2 –

It is then established more enhanced versions of Proportional Conflict Redistribution Rule2 (PCR2). In the PCR2 fusion rule, the total conflicting mass k_{12} is reordered only to the non-empty sets involved in the conflict (not to all non-empty sets as in PCR1) proportionally with respect to their corresponding non-empty column sum in the mass matrix [26]. The redistribution is then more exact (accurate) than in PCR1. A nice feature of PCR2 is the protection of the neutral impact of the VBA and of course its ability to deal with all cases/models.

$m_{PCR2}(\emptyset) = 0,$ (12)

and $\forall Fire \in S^{\Theta} \setminus \emptyset$

and Fire involved in the conflict,

one has $m_{PCR2}(Fire) = \sum_{\substack{X_1,X_2 \in S^{\Theta} \\ X_1 \cap X_2 = Fire}} m_1(X_1)m_2(X_2) + c_{12}(Fire)\frac{c_{12}(Fire)}{e_{12}}.k_{12},$ (13)

while for a set $B \in S^{\Theta} \setminus \emptyset$ not involved in the conflict one has

$m_{PCR2}(Intermediate\ fire) = \sum_{\substack{X_1,X_2 \in S^{\Theta} \\ X_1 \cap X_2 = Intermediate\ fire}} m_1(X_1)m_2(X_2)$ (14)

where

c_{12}(Fire) is the non-zero sum of the column of X in the mass matrix,

i.e., $c_{12}(Fire) = m_1(Fire) + m_2(Fire) \neq 0,$

k_{12} is the total conflicting mass,

e_{12} is the sum of all non-zero column sums of all non-empty sets only involved in the conflict

(in many cases $e_{12} = 2$, but in some degenerate cases it can be less).

In the degenerate case when all column sums of all non-empty sets involved in the conflict are zero, then the conflicting mass is transferred to the non-empty disjunctive form of all sets together which were involved in the conflict. But if this disjunctive form happens to be empty, then one considers an open world and thus all conflicting mass is transferred to the empty set. A non-empty set $X \in S^{\Theta}$ is considered involved in the conflict if there exists another set $Y \in S^{\Theta}$ such that $X \cap Y = 0$ and $m_{12}(X \cap Y) > 0$.

6.4 Proportional Conflict Redistribution rule3 –

In PCR3, one transfers partial conflicting masses, instead of the total conflicting mass, to nonempty sets involved in partial conflict. If an intersection is empty, say $F \cap IF \neq \emptyset$ then the mass $m(F \cap IF)$ of the partial conflict is transferred to the non-empty sets F and IF proportionally with respect to the non-zero sum of masses assigned to F and respectively to IF by the BBA's $m_1(.)$ and $m_2(.)$. The PCR3 rule works if at least one set between F and IF is non-empty and its column sum is non-zero [27].

When both sets F and IF are empty, or both corresponding column sums of the mass matrix are zero, or only one set is non-empty and its column sum is zero, then the mass $m(F \cap IF)$ is transferred to the non-empty disjunctive form $u(F) \cup u(IF)$ defined in equation below; if this disjunctive form is empty then $m(F \cap IF)$ is transferred to the non-empty total ignorance; but if even the total ignorance is empty then either the problem degenerates truly to a void problem and thus all conflicting mass is transferred onto the empty set [28], or can assume that the frame of discernment might contain new unknown hypotheses all summarized by θ_0 and under this assumption all conflicting mass is transferred onto the unknown possible θ_0.

If another intersection, say $A \cap C \cap D = \emptyset$, then again, the mass $m(A \cap C \cap D) > 0$ is transferred to the non-empty sets, A, C, and D proportionally with respect to the non-zero sum of masses assigned to A, C, and respectively D by the sources; if all three sets A, C, D are empty or the sets which are non-empty have their corresponding column sums equal to zero, then the mass $m(A \cap C \cap D)$ is transferred to the non-empty disjunctive form $u(A) \cup u(c) \cup u(D)$; if this disjunctive form is empty then the mass $m(A \cap C \cap D)$ is transferred to the non-empty total ignorance; but if even the total ignorance is empty (a completely degenerate void case) all conflicting mass is transferred onto the empty set (which means that the problem is truly void), or (if we prefer to adopt an optimistic point of view) all conflicting mass is transferred onto a new unknown extra and closure element θ_0 representing all missing hypotheses of the frame Θ. The disjunctive form is defined as:

$u(X) = X\ if\ X\ is\ a\ singleton$

$u(X \cup Y) = u(X) \cup u(Y)$ (15)

$u(X \cap Y) = u(X) \cup u(Y)$ (16)

For the combination of two basic belief assignments, the PCR3 formula is given by: $\forall(X \neq \emptyset) \in G^{\Theta}$

$$m_{PCR3}(X) = [\sum_{\substack{X_1,X_2 \in G^{\Theta} \\ X_1 \cap X_2 = X}} m_1(X_1)\ m_2(X_2)] + [c_{12}(X). \sum_{\substack{Y \in G^{\Theta} \\ Y \cap X = \emptyset}} \frac{m_1(Y)m_2(X) + m_1(X)m_2(Y)}{C_{12}(X) + C_{12}(Y)}]$$

$$+[\sum_{\substack{X_1,X_2 \in (G^{\Theta}\setminus\{X\}) \cap \emptyset \\ X_1 \cap X_2 = \emptyset \\ u(X_1)\cup u(X_2) = X}} [m_1(X_1)\, m_2(X_2) + m_1(X_2) m_2(X_1)]] +$$

$$[\, \phi_{\Theta}(X) \sum_{\substack{X_1,X_2 \in (G^{\Theta}\setminus\{X\}) \cap \emptyset \\ X_1 \cap X_2 = \emptyset \\ u(X_1) = u(X_2) = \emptyset}} [m_1(X_1)\, m_2(X_2) + m_1(X_2) m_2(X_1)]] \quad (17)$$

where all sets are in canonical form, $c_{12}(X_i)\ (X_i \in G^{\Theta})$ is the non-zero sum of the mass matrix column corresponding to the set X_i, i.e. $c_{12}\ (X_i) = m_1(X_i) + m_2(X_i) \neq 0$, and where $\phi_{\Theta}(.)$ is the characteristic function of the total ignorance defined by $\phi_{\Theta}(X) = 1\ if\ X = \Theta \triangleq \theta_1 \cup \ldots \cup \theta_n$ (full ignorance); $\phi_{\Theta}(X) = 0$ otherwise. PCR3 preserves the neutral impact of the VBA and works for any cases/models.

6.5 Algorithm for PCR3 –

1. Generate the mass matrix related with the beliefs assignments $m_1(.)$ and $m_2(.)$

   $m_1 = [m_1(\theta_1) m_1(\theta_2) m_1(\theta_3)]$

   $m_2 = [m_2(\theta_1) m_2(\theta_2) m_2(\theta_3)]$

2. Then fusion of two sources is done

   $$M_{12} = \begin{bmatrix} m_1 \\ m_2 \end{bmatrix} = \begin{bmatrix} m_1(\theta_1) & m_1(\theta_2) & m_1(\theta_3) \\ m_2(\theta_1) & m_2(\theta_2) & m_2(\theta_3) \end{bmatrix}$$

3. Conjunctive consensus is calculated using the formula

   $m_{\cap}(.) = [m_1 \oplus m_2]\ (.)$

   $m_{\cap}(X) = \sum_{A,B \in G^{\Theta}} m_1(A)\, m_2(B)$

4. Compute the conjunctive masses $C_{12}(X)$

   $c_{12}(X = \theta_1) = m_1(\theta_1) + m_2(\theta_1)$

   $c_{12}(X = \theta_2) = m_1(\theta_2) + m_2(\theta_2)$

   $c_{12}(X = \theta_3) = m_1(\theta_3) + m_2(\theta_3)$

5. Now, redistribute the conflicting mass proportionally

   $$m_{PCR3}(X) = [\sum_{X_1,X_2 \in G^{\Theta}} m_1(X_1)\ m_2(X_2)\,] + [\ c_{12}(X). \sum_{X_1,X_2 \in G^{\Theta}} \frac{m_1(Y) m_2(X) + m_1(X) m_2(Y)}{C_{12}(X) + C_{12}(Y)}\,]$$

7. EXPERIMENTAL RESULTS AND ANALYSIS

The data sets which are used in this analysis are the inert data collected from the forest department. A sample of 200 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 and test 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 1. 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 Table 1.

Table -1 Output from the Classifiers

Classifiers	Fire	Intermediate Fire	No Fire
SVM Polynomial	0.55	0.35	0.1
SVM RBF ($\sigma = 0.3$)	0.43	0.57	0.2
SVM RBF (σ=0.9999)	0.41	0.39	0.2

From the Table 1, fusion of three classifiers using Proportional Conflict Redistribution rule of combination was deliberated and the values of mass for Fire, Intermediate Fire and No Fire are calculated. Using the Proportional Conflict Redistribution rule 1 and rule 2, the total conflicting mass, K_{12} is calculated to be 0.63. The belief of fire (F), intermediate fire (IF) and no fire (NF) are calculated as Bel(F) = 0.51, Bel(IF) = 0.37 and Bel(NF)=0.12. The highest value of belief is taken as the decision of PCR1 and PCR2. If one applies the Proportional Conflict Redistribution rule 1 and rule 2, it affords a reliable and judicious solution to the combination of conflict resources. While using the Proportional Conflict Redistribution rule 3 the conjunctive consensus is calculated as $m_{\cap}$(F)=0.2287, $m_{\cap}$(IF) = 0.1385, $m_{\cap}$(NF) = 0.0175. From this, the belief of F, IF and NF are calculated as Bel(F)=0.55, Bel(IF) = 0.37 and Bel(NF) = 0.08. The highest value of belief is taken as the decision of PCR3 and the above values are shown in Table 2.

Table -2. Accuracy of PCR1, PCR2 and PCR3 in %

Engine	Fire	Intermediate Fire	No Fire
PCR1 & PCR2	51 %	37 %	12 %
PCR3	55 %	37 %	8 %

From the Table 2 it is perceived that the accuracy of PCR3 is more than that of PCR1 and PCR2 and the values are plotted in the graph as shown in Figure 1.

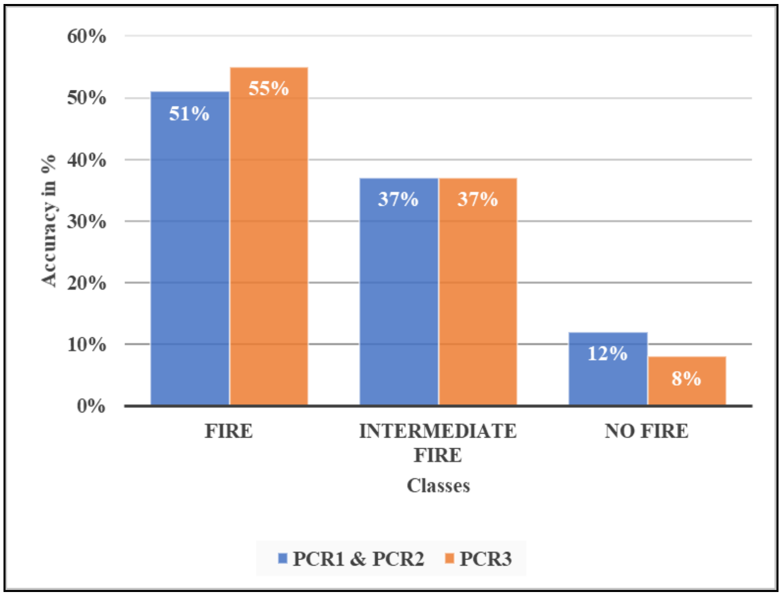

Figure 1. Comparision of PCR1, PCR2 and PCR3

7.1 Experimental Analysis of PCR1, PCR2 and PCR3 rule for failure in WSNs –

When there is a link / node failure in the wireless sensor network, the masses generated from the three classifiers are shown in Table 3

Table -3. Output from the Classifiers

Classifiers	Fire	Intermediate Fire	No Fire
SVM Polynomial	0.90	0	0.1
SVM RBF (σ = 0.3)	0.43	0.57	0
SVM RBF (σ=0.9999)	0.41	0.39	0.2

From the above masses, the belief masses of PCR3 with and without node / link failure are intended. The basic belief mass function with the PCR3 rule of combination is calculated to be $m_{PCR3}(F) = 0.5462$; $m_{PCR3}(IF) = 0.3732$; $m_{PCR3}(NF) = 0.0807$. Conclusively, using PCR3 rule, the accuracy is calculated to be Fire = 55%, Intermediate Fire=37% and No Fire = 8%. Even if there is a node / link failure it is acknowledged that the accuracy of PCR3 is more than that of PCR1 and PCR2 for the above dataset in the scheme of detection of fire in the forest.

8. CONCLUSION

We have presented in this paper three versions of the Proportional Conflict Redistribution rule of combination for information fusion in the context of forest fire detection. PCR1 and PCR2 redistribute the total conflicting mass, while PCR3 redistribute partial conflicting masses. All the PCR rules proposed in this paper preserve the neutral impact of the vacuous belief assignment. Therefore, considering the way each rule works, the rule PCR3 is considered better than other rules PCR1 and PCR2 in terms of accuracy in the context of forest fire detection. There is no change in accuracy even in the case of node/ link failure while using PCR3, which is more suitable for fire detection in the forest.

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