Image Features As a Feed To Rough Sets for Fire/Smoke Detection

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Abstract

Many researchers are being involved in fire detection using camera images as information data. However earlier researches have not paid attention to the determination of the type of fire (naked or smoldering). This paper proposes an improved fire detection method based on the image features that are taken as a feed to a rough set information system (RSIS) in order to not only determine the type of the fire but also to minimize the false alarm signals from the methods based on physical aspects of fire (temperature, smoke sensors, etc.) and other frequency based image features WMF(Wavelet-based model) and FDS(Fire detection based on discrete cosine coefficients) proposed earlier.

Keywords: *Image processing, fire detection, computer vision, information system.*

1. Introduction

Fire hazards are becoming ones of the most important fears of mankind. Many researchers are now studying a decision-making method for fire detection data fusion based on rough set approach by introducing an attribute reduction method based on the characteristics of consistent approximation space (CAS) of rough set as stated in[3]. This paper considers an image information data and contributes to the choice of image data attributes to simulate that consistent approximation space. As nowadays alarming on the indoor fire is relatively being mature, fire detectors have been divided into different categories such us: SSD-Smoke Sensing Detectors, TSD-Temperature sensing detectors and LSD-Light Sensing Detectors [3]. All these types of fire have different levels of detection to tract out the type and the stage of fire. Due to space constraints the types enumerated above can have difficulties in timely detecting fires that are very distanced from the sensors. Therefore, using cameras to detect fire can greatly improve the situation of producing false alarming signals and increase the safety by granting a quicker response.

2. Related works

Many fire detection systems that use conventional smoke detection systems depend on point smoke detectors in order to test the presence of some particles generated by smoke using ionization or photometry. However, such point detectors inherently suffer from the transport delay of the smoke from the fire to the sensor[12]. Many improvements that use computer vision are based on the color cues of fire, and the fact that color is very sensitive to illumination changes[10-11] proves that frequency domain features could be more reliable cues than color in general situations, the reason why a new colour-based model of fire’s appearance as well as a new wavelet-based model of fire’s frequency signature were proposed in [8] and another one based on discrete cosine coefficients trained with neural networks were proposed in [9]. This paper proposes an improvement by an attribute reduction method based on the image features taken as a feed to a rough set information data (RSFD), by using image information fusion techniques that would involve information processing, pattern recognition, and decision process. The information can be fused at data layer, feature layer and decision layer in the time domain, spatial domain, or other domains, the most important contribution is to even determine the type of fire (smoldering or naked) so that the fire can be dealt with accordingly.

3. Image as a Rough Set Data Information.

3.1 The choice of Rough Sets

Fire types are varied in nature leading to an information redundancy and uncertainty. It is then necessary to find a tool that can deal with such a challenge. Rough Set theory proposed by Pawlak is one of the first non-statistical approaches for such data analysis in one of its fundamental concepts which is knowledge reduction for data classification .

3.2 Representation of Image as a rough set information

Image data (features) can be considered as an information system, decision system or inconsistent decision information system in order to be dealt with by the means of rough set technique. If the attribute reduction methods and attributes features in the sample images are defined, we can then get attribute reduction methods and attributes features in all other images to be investigated.

The decision rules can be obtained through the fusion of training data sets.

Definition 1: Let U={x1,x2,…,xn} be an object set, and A= {a1,a2,…an} be an attribute set,

£ = {Ra ⊆ U×U /a ∈ A } is a family of equivalence relations on U, Ŕ is an equivalence relation on U, then we can define (U,A,£,Ŕ) as a consistent information system of our image. To obtain decision rules, the relationship between two different families of relationships needs to be identified [1]. The concept of the image information data will be introduced to find this connection between the two equivalence relations, which is the basis of deriving the overall relationship from a family of relationships.

Definition 2: Let S = (U,A,£,Ŕ) be our image information system; then $R_B = \bigcap_{a \in B} R_a (B \subseteq A)$.

If Ra ⊆ Ŕ then S is consistent information system for our image.

If RB ⊆ Ŕ(B ⊆ A), where B is an attribute consistent set of S, and any real subset of B is not attribute consistent set, then B is attribute reduction set of S[4][2].

We can always get decision rules for a given Image. However, these rules are applicable for decision in partial conditions, not for all the combinations of different conditions. Fortunately, rules fusion can offer as much decision rules under different conditions as possible with a limited number of existing rules.

3.3 Rules fusion in the Image Information System

For an image information system (U,A,£,Ŕ), Ra ⊆ Ŕ, if B is an attribute consistent set, then RB ⊆ Ŕ Suppose U/RB={[Xi]B / Xi ∈ U}

U/ Ŕ={D1,D2…Dr} because RB ⊆ Ŕ then, for any Xi ∈ Dj, let [Xi]B ⊆ Dj, then we have a decision rule: "If x ∈ [Xi]B, then the decision is D_j". The attribute reduction method is shown as follows [3]:

Divide U into equivalence classes using ŔU/ Ŕ={D_1,D_2,…D_r}

For D_j(j<r), denoted M_j={($f_1(x_i)$)}, ={($f_2(x_i)$)}, … ={(fm(x_i))} / [x_i]A ⊆ D_j)} (j≤r)

Union of elements in M_j, we have $F_j = \{F_1^j, F_2^j, \ldots F_m^j\}$ (j≤r)

For any, $v_1 \in V_1$ l≤r, denoted E = {v_1}, {v_2},…{v_l}

computing $D(F_{jo}/E) = \underset{j \le m}{Max} D(F_j/E)$ Then we get rule: "If $\bigwedge_{l=1}^{m} (a_l, v_l)$ then $D_{j0}(D\left(\frac{F_{jo}}{E}\right))$.

4. Selection of Fire Alarm Signal Based on Statistical Characteristics

Being concerned about knowing which kind of image attribute and the number of attributes that are selected for different kinds of fire, if the selected attribute type is of too small importance, it is hard to distinguish different types of fire and non-fire source. On the other hand, larger types of attributes lead to a lot of data redundancy, and will increase the complexity of the fusion process. It is well known that fire has unique visual signatures. Randomness, boundary roughness and skewness can be powerful discriminants fort classification because of flickering and random characteristics of fire as stated in [5] which is the reason why we consider them as the three fire detector parameters in order to collect the fire information for the data fusion.

5. Applicational experiment

5.1 Example data

FIGURE 1: Background, with fire and k-means segmented image

Xn record is given by first segmenting an image with k-means to find a new object which is then extracted from the background image (figure 1) and the image of the extracted object (figure 3) gives the attributes for every Xn record.

To judge the performance of the proposed method, we select a group of real fires to demonstrate its capability. When this group of fire data is expanded, in other words if we get [illegible] detection data, the method can then be [illegible]ta and to derive decision rules as shown in Table I.

Table 1 .Sample of data record

Serial No ***U***	***Input Data***			***Fire Probability***	
	Randomness a1	*Boundary Roughness a2*	*Skewness a3*	*Naked d1*	*Smoldering d2*
X1	0.1	1.0	0.0	0.7	0.9
X2	0.3	1.0	0.5	0.9	0.9
X3	0.1	0.2	0.0	0.3	0.4
X4	0.5	0.8	0.8	0.8	0.7
X5	0.0	0.1	0.3	0.1	0.1
X6	0.0	1.0	0.3	0.1	0.1
X7	0.0	0.0	1.0	0.2	0.1
X8	0.3	0.5	0.2	0.7	0.3
X9	0.6	0.8	0.8	1.0	0.1
X10	0.2	0.3	0.0	0.6	0.8

5.2 Statistical Interpretation

To calculate the probability of naked fire, according to different steps in the image information system fusion, from Table I we get:

For the first step:

$U/d_1=\{\{X_5,X_{11}\},\{X_7\},\{X_3\},\{X_6\},\Phi,\{X_{10}\},\{X_1,X_8,X_{12},\{X_4\},\{X_2\},\{X_9\}\}$

Denoted:

$D_0 = \Phi$, $D_1 = \{X_5,X_{11}\}$, $D_2 = \{X_7\}$, $D_3 = \{X_3\}$, $D_4 = \{X_6\}$, $D_5 = \Phi$, $D_6 = \{X_{10}\}$,

$D7 = \{X_1,X_8,X_{12}\}$, $D_8 = \{X_4\}$, $D_9 = \{X_2\}$, $D_{10} = \{X_9\}$

D_i represents the probability of naked fire, with a value range from 0.0 to 1.0.

For the second step:

$M_1 = \{(0.0\}, \{0.1\}, \{0.3\}, \{0.1\}, \{0.1\}, \{0.0\})\}$;$M_2 = \{(0.0\}, \{0.0\}, \{1.0\})\}$;$M_3 = \{(0.1\}, \{0.2\}, \{0.0\})\}$;$M_4 = \{(0.0\}, \{1.0\}, \{0.0\})\}$;$M_6 = \{(0.2\}, \{0.3\}, \{0.0\})\}$;$M_7 = \{(\{0.1\}, \{1.0\}, \{0.0\}), (\{0.3\}, \{0.5\}, \{0.2\}), (\{0.4\}, \{0.0\}, \{0.2\})\}$;$M8 = \{(0.5\}, \{0.8\}, \{0.1\})\}$;$M_9 = \{(0.3\}, \{1.0\}, \{0.5\})\}$;$M_{10} = \{(0.6\}, \{0.8\}, \{0.8\})\}$

For the third step, union of elements in Mj, we have

$F_1 = (\{0.0,0.1\}, \{0.1\},\{0.0,0.3\})$; $F_2 = (\{0.0\},\{0.0\},\{1.0\})$; $F_3 = (\{0.1\}, \{0.2\}, \{0.0\}$; $F_4 = (\{0.0\}, \{1.0\}, \{0.0\}$; $F_6=(\{0.2\},\{0.3\},\{0.0\}$; $F_7=(\{0.1,0.3,0.4\},\{0.0,0.5,1.0\},\{0.0,0.2\}$

$F_8 = (\{0.5\} ,\{0.8\}, \{0.1\}$; $F_9 = (\{0.3\}, \{1.0\}, \{0.5\}$; $F_{10}=(\{0.6\},\{0.8\},\{0.8\}$

For the fourth step, given E = $E=(\{0.1\},\{0.8\},\{0.2\})$, then $D(F_1/E)=2/5$, $D(F_2/E)=0$, $D(F_3/E)=1/3$, $D(F_4/E)=0$, $D(F_5/E)=0$, $D(F_6/E)=0$, $D(F_7/E)=5/8$, $D(F_8/E)=1/3$, $D(F_9/E)=0$, $D(F_{10}/E)=1/3$

Finally, we get the following rule :

"If (a1,0.1) $\wedge$ (a2,0.8) $\wedge$ (a3,0.2), then D=0.7(5/8)", value 5/8 is the confidence of the rule. That is, when the randomness attributes gives value 0.1,the boundary roughness gives value 0.8, the skewness gives value 0.2, and the probability of naked fire is 0.7.

Similarly, the probability of the smoldering fire can be shown as follows:

$D(F_1/E)=3/5$, $D(F_2/E)=1/3$, $D(F_3/E)=1/3$, $D(F_4/E)=1/3$, $D(F_5/E)=0$, $D(F_6/E)=0$, $D(F_7/E)=1/3$, $D(F_8/E)=0$, $D(F_9/E)=1/3$, D

$(F_{10}/E)=0$ and we get the following rule "If (a_1, 0.1) $\wedge$ (a_2, 0.8) $\wedge$ (a_3,0.2), then D=0.1 (3/5) ", value 3/5 is the confidence of the rule. That is, when the randomness attribute gives a value of 0.1, the boundary roughness gives a value of 0.8, the skewness gives a value of 0.2, and the probability of smoldering fire is 0.1.

To conclude, with the randomness value of 0.1, the boundary roughness value of 0.8, and the skewness value of 0.2, the probability of naked fire is 0.7 while the probability of smoldering fire is 0.1

5.3 Discussion on Results

To interpret the results of this method, we considered that if the probability of an image to contain fire is 0.5 or higher, then the image has fire. 500 images with smoldering fire and 500 images with naked fire and 1000 images without fire were used for testing the proposed method. The different environments we used are candles light, electrical tubes light, paper fire and plastic fire in night shots and day time shots to gain the variability. Another source of frames has been taken from the indoor video clips from Signal and Image Processing Group at Bilkent University in Turkey

(http://signal.ee. bilkent.edu.tr/VisiFire/Demo/FireClips/) and we compared the results with a Background Binary Mask denoted as BBM used with statistical color model as it has been developed on the same environments[6] and then we compared our results with a wavelet-based model of fire's frequency signature denoted as WMF[8] and FDS(Fire detection based on discrete cosine coefficients)[9] .

From the results presented in Table II, out of 1000 images containing fire(positive images), the WMF, FDS and RSFD counted up to 850,890 and 910 images respectively, which means that RSFD outperforms the WMF and FDS by 6% and 2% respectively. Out of 1000 images without fire(negative images), WMF, FDS and RSFD counted up to 860, 870 and 900 images respectively, which shows that RSFD outperforms the WMF and FDS by 4% and 3% respectively. From the results, it is clear that the RSFD based fire detection presented an advantage of getting more positive images as shown by the three different judging methods: accuracy, sensitivity and specificity, which were used as defined in equation (1), (2) and (3)[9].

Table 2. Detailed comparative analysis.

	Positive images		***Negative images***		***Performance***		
Method	*Detected positive images*	*False negative images*	*Detected negative images*	*False positive images*	*Accuracy*	*Sensitivity*	*Specificity*
WMF[8]	85%	15%	86%	14%	85	0.85	0.86
FDS[9]	89%	11%	87%	13%	88	0.89	0.87
RSFD	91%	9%	90%	10%	89	0.89	0.88

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} x100\% \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

Where TP, TN, FP and FN are true positive, true negative, false positive, and false negative.

6. Conclusion

Rough set theory being a good mathematical tool used for data classification, can effectively solve fire false alarms problems taking image features as data information into account. After image data is represented as rough set information data, we can fuse the fire detection data and get the reliability of fusion calculation as well.

To check the robustness of the used technique, we compared our results to those from the wavelet-based model of fire's frequency signature (WMF) and FDS(Fire detection based on discrete cosine coefficients). The averaged overall accuracy is about 5% better than that of WMM and 3% better than that of FDS. The sensitivity of 0.89 and specificity of 0.88 shows that this method can be smart enough for fire detection. Nevertheless, computing accuracy is strongly linked to how many sample data we have. A sufficient number of sample sets are needed in order to guarantee an improvement of the precision.

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