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An Improvement of Type-2 Fuzzy Clustering Algorithm for Visual Fire Detection

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Abstract: **This paper presents a novel approach for visual fire detection by modelling the spatial structure of fire, this structure is considered in terms of the color intensity of fire-color pixels. To model this structure, the authors uses an interval type-2 fuzzy clustering algorithm with some modification to separate fire-color pixels into some clusters, then these clusters are used to model the structure of fire. Experimental results show that our method is capable of detecting fire in early state and in the weak light-intensity environment. In addition, this method evaluates the structure of fire from a single image, so it can be integrated into the surveillance system or applied in automated retrieval of events in newscast videos in which the camera is dynamic.**
Keywords: Visual fire detection, type-2 fuzzy clustering, type-2 fuzzy sets

I. Introduction

In the last ten years a large number of vision based fire detection systems are introduced due to the rapid development in digital camera technology and advances in content-based video and image processing. Vision based systems generally make use of three characteristics of fire: color, motion and geometry. In Healey et al. [1], authors determinate fire rely on movement and color alone. Phillips et al. [2], used color predicate information and the temporal variation of a small subset of images to recognize fire in video sequences; a manually segmented fire set is used to train a system that recognizes fire like color pixels and the results is used to form a look-up table for the fire detection system. Liu and Ahuja [3], proposed a vision based fire detection algorithm based on spectral, spatial and temporal properties of fires; analysis of the temporal fire variation to allow for the fact that fire flickers. Chen et al. utilized a change detection scheme to detect flicker in fire regions [4]; the moving objects were filtered with fire and smoke filter to raise an alarm for possible fire in video and they used a generic fire and smoke model to construct the corresponding filter. Toreyin et al. [5], proposed an algorithm which combines a generic RGB color model, motion information and Markov process enhance fire flicker analysis; in another proposal they presented a real-time algorithm for fire detection in video sequences [6], combine of motion and color clues with fire flicker analysis on a wavelet domain. Celik et al. proposed a generic model for fire color [7]; the authors combined their model with simple moving object detection in order to detect fires in video. In [8], they developed two models based on luminance and chrominance in which fuzzy logic are used to replace existing heuristic rules and make the classification in discriminating fire and fire like colored objects. Nicholas True [9], used multi-feature classification approach for detecting fire in video data, they introduced the concept of dynamic texture analysis to the existing body of video-based fire detection research and show that it works well in concert with other tried and true fire feature detection algorithms. In [12], the authors also used a probabilistic metric to threshold potential fire pixels. This was achieved by multiplying the probabilities of each individual color channel being fire. In [13], Chao-Ching Ho analysed the spectral, spatial and temporal characteristics of the flame and smoke regions in the image sequences.

Type-2 fuzzy logics with the capability of handing the uncertainty are widely applied in many fields [18], [19], especially pattern recognition [20]. Clustering algorithms have developed for applications of pattern recognition in different approaches. The family of k-mean clustering algorithms has archived positive results with refinements such as identifying the number of clusters [25]. Type-2 fuzzy cmean clustering [23], [24] is an extension of fuzzy c-mean algorithm with identifying FOU of fuzzifiers, resulting to handling uncertainty is better.

The paper deals with a refinement algorithm of type-2 fuzzy c-mean clustering with initial step is to find rough center of clustering and identifying the number of clusters. This paper also proposes a new approach for visual fire detection problem by using interval type-2 fuzzy sets in clustering algorithm for fire-color pixels in RGB color space. The model of fire is built on the results of clustering includes some attributes of the clusters: number of clusters, number of pixels, shape and location of each cluster. The proposed approach is experimented with two data-sets to show fire will be detected early for alarming in weak light-intensity environment.

The paper is organized as follows. Section II-A introduces briefly type-2 fuzzy sets and operators. The implementation of interval type-2 fuzzy clustering is presented in section II-B. The new algorithm is described in section III, IV; in these the model of fire presents in section III and completed algorithm in section IV. The experimental results are shown in section V and the section VI ware conclusions.

II. Background

A. Type-2 Fuzzy Sets

A type-2 fuzzy set in X is $\tilde{A}$, and the membership grade of $x \in X$ in A is $\mu_{\tilde{A}}(x,u), u \in J_x \subseteq [0,1]$, which is a type-1 fuzzy set in [0, 1]. The elements of the domain of $\mu_{\tilde{A}}(x,u)$ are called primary memberships of x in $\tilde{A}$ and the memberships of the primary memberships in $\mu_{\tilde{A}}(x,u)$ are called secondary memberships of x in $\tilde{A}$.

Definition II.1 *A $type-2$ $fuzzy$ set, denoted $\tilde{A}$, is characterized by a type-2 membership function $\mu_{\tilde{A}}(x,u)$ where $x \in X$ and $u \in J_x \subseteq [0,1]$, i.e.,*

$$\tilde{A} = \{((x,u), \mu_{\tilde{A}}(x,u)) | \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \quad (1)$$

or

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \mu_{\tilde{A}}(x,u))/(x,u), J_x \subseteq [0,1] \quad (2)$$

in which $0 \leq \mu_{\tilde{A}}(x,u) \leq 1$.

At each value of x, say $x = x'$, the 2-D plane whose axes are u and $\mu_{\tilde{A}}(x',u)$ is called a $vertical\ slice$ of $\mu_{\tilde{A}}(x,u)$. A *secondary membership function* is a vertical slice of $\mu_{\tilde{A}}(x,u)$. It is $\mu_{\tilde{A}}(x = x', u)$ for $x \in X$ and $\forall u \in J_{x'} \subseteq [0,1]$, i.e.

$$\mu_{\tilde{A}}(x = x', u) \equiv \mu_{\tilde{A}}(x') = \int_{u \in J_{x'}} f_{x'}(u)/u, J_{x'} \subseteq [0,1] \quad (3)$$

in which $0 \leq f_{x'}(u) \leq 1$.

According to representation based on embedded fuzzy sets, a type-2 fuzzy sets ([18],[19]) is union of its type-2 embedded sets, i.e

$$\tilde{A} = \sum_{j=1}^{n} \tilde{A}_e^j \quad (4)$$

where $n \equiv \prod_{i=1}^{N} M_i$ and $\tilde{A}_e^j$ denoted the j^{th} type-2 embedded set for $\tilde{A}$, i.e.,

$$\tilde{A}_e^j \equiv \{\left(u_i^j, f_{x_i}(u_i^j)\right), i = 1,2,...,N\} \quad (5)$$

where $u_i^j \in \{u_{ik}, k = 1,...,M_i\}$.

Type-2 fuzzy sets are called an interval type-2 fuzzy sets if the secondary membership function $f_{x'}(u) = 1\ \forall u \in J_x$ i.e. a type-2 fuzzy set are defined as follows:

Definition II.2 *An interval type-2 fuzzy set $\tilde{A}$ is characterized by an interval type-2 membership function $\mu_{\tilde{A}}(x,u) = 1$ where $x \in X$ and $u \in J_x \subseteq [0,1]$, i.e.,*

$$\tilde{A} = \{((x,u), 1) | \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \quad (6)$$

Uncertainty of $\tilde{A}$, denoted FOU, is union of primary functions i.e. $FOU(\tilde{A}) = \bigcup_{x \in X} J_x$. Upper/lower bounds of membership function (UMF/LMF), denoted $\overline{\mu}_{\tilde{A}}(x)$ and $\underline{\mu}_{\tilde{A}}(x)$, of $\tilde{A}$ are two type-1 membership functions and bounds of FOU.

B. Interval Type-2 Fuzzy Clustering Algorithm

IT2FCM is extension of FCM clustering by using two fuzziness parameters m_1, m_2 to make FOU, corresponding to upper and lower values of fuzzy clustering. The use of fuzzifiers gives different objective functions to be minimized as follows:

$$\begin{cases} J_{m_1}(U,v) = \sum_{k=1}^{N} \sum_{i=1}^{C} (u_{ik})^{m_1} d_{ik}^2 \\ J_{m_2}(U,v) = \sum_{k=1}^{N} \sum_{i=1}^{C} (u_{ik})^{m_2} d_{ik}^2 \end{cases} \quad (7)$$

in which $d_{ik} = \parallel x_k - v_i \parallel$ is Euclidean distance between the pattern x_k and the centroid v_i, C is number of clusters and N is number of patterns. Upper/lower degrees of membership, $\overline{u}_{ik}$ and $\underline{u}_{ik}$ are determined as follows:

$$\overline{u}_{ik} = \begin{cases} \dfrac{1}{\sum_{j=1}^{C} (d_{ik}/d_{jk})^{2/(m_1-1)}} & if\ \dfrac{1}{\sum_{j=1}^{C} (d_{ik}/d_{jk})} < \dfrac{1}{C} \\ \dfrac{1}{\sum_{j=1}^{C} (d_{ik}/d_{jk})^{2/(m_2-1)}} & if\ \dfrac{1}{\sum_{j=1}^{C} (d_{ik}/d_{jk})} \geq \dfrac{1}{C} \end{cases} \quad (8)$$

$$\underline{u}_{ik} = \begin{cases} \dfrac{1}{\sum_{j=1}^{C} (d_{ik}/d_{jk})^{2/(m_1-1)}} & if\ \dfrac{1}{\sum_{j=1}^{C} (d_{ik}/d_{jk})} \geq \dfrac{1}{C} \\ \dfrac{1}{\sum_{j=1}^{C} (d_{ik}/d_{jk})^{2/(m_2-1)}} & if\ \dfrac{1}{\sum_{j=1}^{C} (d_{ik}/d_{jk})} < \dfrac{1}{C} \end{cases} \quad (9)$$

in which $i = \overline{1,C}$, $k = \overline{1,N}$.

Because each pattern has membership interval as the upper $\overline{u}$ and the lower $\underline{u}$, each centroid of cluster is represented by the interval between v^L and v^R. Cluster centroids are computed in the same way of FCM as follows:

$$v_i = \frac{\sum_{k=1}^{N} (u_{ik})^m x_k}{\sum_{k=1}^{N} (u_{ik})^m} \quad (10)$$

in which $i = \overline{1,C}$ (detail in [23]).

After obtaining v_i^R, v_i^L, type-reduction is applied to get centroid of clusters as follows:

$$v_i = (v_i^R + v_i^L)/2 \quad (11)$$

For membership grades:

$$u_i(x_k) = (u_i^R(x_k) + u_i^L(x_k))/2, j = 1,...,C \quad (12)$$

in which

$$u_i^L = \sum_{l=1}^{M} u_{il}/M, u_{il} = \begin{cases} \overline{u}_i(x_k) & \text{if } x_{il} \text{ uses } \overline{u}_i(x_k) \text{ for } v_i^L \\ \underline{u}_i(x_k) & otherwise \end{cases} \quad (13)$$

$$u_i^R = \sum_{l=1}^{M} u_{il}/M, u_{il} = \begin{cases} \overline{u}_i(x_k) & \text{if } x_{il} \text{ uses } \overline{u}_i(x_k) \text{ for } v_i^R \\ \underline{u}_i(x_k) & otherwise \end{cases} \quad (14)$$

Next, defuzzification for IT2FCM is made as if $u_i(x_k) > u_j(x_k)$ for $j = 1,...,C$ and $i \neq j$ then x_k is assigned to cluster i.

III. Fire model

In this proposal, we consider the problem of fire detection in environments with weak light-intensity and in the early states of fire; in these conditions, the flame is small and brighter than the background. Our method uses the clustering technique described in section II.B with some modification for each single image (see IV.A). The results of clustering is then considered by the fire model for detecting fire. A fire-alarm is given when the alarm-raising.
The fire region in a single image can be modeled as follows: (i) It has a high contrast to its surroundings; (ii) It exhibits a structure of nested rings of colors, changing from white at the core to yellow, orange and red in the periphery.

A. Environment with weak-light intensity

As mentioned above, this study focuses on solving problems in condition of weak light-intensity environments. Visually, the video can be classified according to levels of the ambient light: weak, moderate or strong. Environmental conditions of weak light can be seen in the video recording at night, in a closed room, in low light, .etc. These are fairly common situations in practice for problem detection and fire observation. Using a gray-level histogram we can analysis the

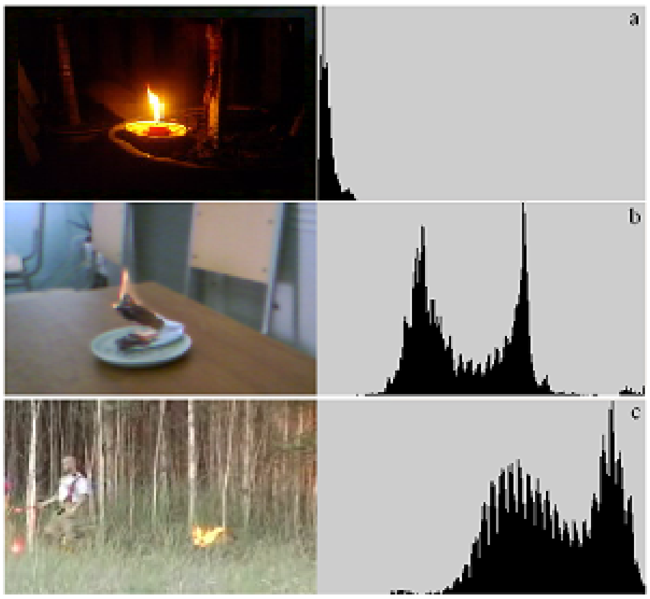

Figure. 1: The images from the video frame and its gray-level histogram

environmental light conditions. Figure 1 illustrates the histograms of the three images in different lighting conditions, (a) - Photos took in weak light-intensity environments, gray level histogram is located on the left, (b) - Photographs of the normal environment, the histogram is the gray balance in the horizontal axis, (c) - Photographs of outdoor lighting conditions to at sunny, histogram is located on the right. Denoted $p(r)$ is a normalized histogram of gray image f, we have:

$$p(r) = \frac{n_r}{n} \tag{15}$$

where $r \in [0.1, ..., L]$, and L is the largest gray level in images, n_r is the total number of pixels with gray level equal to r and n is the total number of pixels of the image f. Easy to see that, in low light conditions, the average value of gray levels is small, and also image the surface structure will be relatively homogeneous. The average value calculated by:

$$M = \sum_{r=0}^{L} r * p(r) \tag{16}$$

and the uniformity on the image by:

$$Un = \sum_{r=0}^{L} p(r) * p(r) \tag{17}$$

Based on the parameters M and Un to conclude f photo was taken in low light conditions if:

$$\begin{cases} M \leq M_0 \\ Un \geq Un_0 \end{cases} \tag{18}$$

where M_0 and U_0 are the values of a predetermined threshold. Suggested experimental values $M_0 \in [80, 90]$ and $Un_0 \in [0.05; 0.07]$ for the relatively good results. Experiments in this paper use the value of $M_0 = 85$, and $Un_0 = 0.06$.

B. Spatial structure of fire

After clustering the fire we generally have a spatial structure as Figure 2. The structure of fire in this proposal is a combination of the number of clusters and their number points, the position and the distributed of each class around their center.

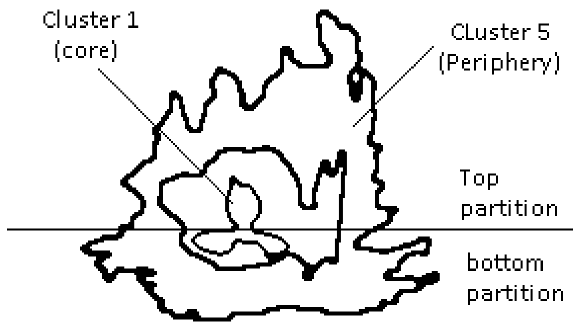

Figure. 2: The spatial structure of clusters

1) Number of clusters and their number points

For each pixel in image, three values of RED, GREEN and BLUE channels are used to cluster. We cluster all pixels of the image in a RGB space into six clusters. The dark cluster is ignored because it is the background of image; five other clusters may belong to the fire blob, these clusters are numbered from 1 to 5 respectively as illustrated in Figure 2.
Approximately, probability of each pixel in fire blob belong to cluster number i is as:

$$c_i = \frac{n_i}{n} \tag{19}$$

where $i \in \{1, 2, 3, 4, 5\}$, n_i is the total number of pixels of cluster ith and n is the total number of pixels of fire blob. The

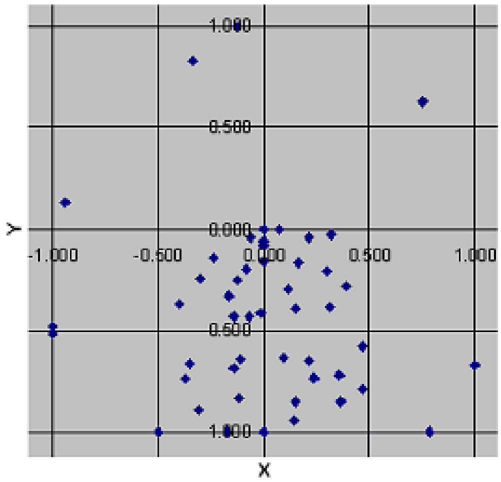

Figure. 3: The position of the clusters

statistical analysis of probability of five clusters in fire pixels over a large set of images is performed. For this purpose a set which consists 765 images at different resolutions are collected from internet. The collected set of images has a wide range of illumination and camera effects. The result of analysis is reported in Table 1.

Table 1: Probability of five cluster pixels of fire

Cluster	C_1	C_2	C_3	C_4	C_5
$c_i^l - c_i^h$	0.01-0.17	0.02-0.22	0.04-0.26	0.11-0.37	0.27-0.57

Then, the single image f is considered having fire if the probability of each of five clusters satisfies:

$$c_i^l \leq c_i \leq c_i^h \tag{20}$$

2) The positions of clusters in the image space

Perform the experiments described above and the relationship of positions between cluster C_1 and the clusters remains in the image space as follows: to translate the cluster i into (x_1, y_1) by $(x_i = x_i - x_1, y_i = y_i - y_1)$; and normalization the distance from each cluster i and (x_1, y_1) by $(x_i = x_i/M, y_i = y_i/M)$, where M=Max$(\{x_i\}, \{y_i\})$ and $i = 1, 2, 3, 4, 5$. The results are shown in Figure 3. It is easy to recognize that most the centroids of clusters are located in the rectangle by $x = [-0.5, 0.5]$ and $y = [0, -1]$. Additional criteria for fire in single image f if:

$$\begin{cases} -0.5 \leq x_i \leq 0.5 \\ 0.0 \leq y_i \leq -1.0 \end{cases} \tag{21}$$

with (x_i, y_i) is the location of center of cluster C_i.

3) The distribution of a cluster around their centroids

The last feature of fire is symmetric to the center of fire. We modeled this feature by dividing the image space into two partitions as in Figure 2: Top and Bottom partitions. Call N_i^T and N_i^B are numbers of pixels of fire blob in the top and bottom partitions of ith cluster; Considered the ratio of Top-Cluster symmetry s_i defined by $s_i = N_i^T/(N_i^T + N_i^B)$. Do the same method has been used in section 1). The results of analysis are in Table 2. Then, another additional condition to prove the single image f has fire if:

Table 2: The ratio of Top-Cluster symmetry

Cluster	C_1	C_2	C_3	C_4	C_5
$s_i^l - s_i^h$	0.06-0.61	0.12-0.68	0.03-0.71	0.06-0.65	0.12-0.68

$$s_i^l \leq s_i \leq s_i^h \tag{22}$$

Finally, the image f with clusters $C_i, i = 1, 2, 3, 4, 5$ has fire alarm if these equations (20),(21) and (22) are satisfied.

IV. Algorithm

A. Improved interval type-2 fuzzy C means algorithm - IT2FCM

In this section, we represent some improvements of interval type-2 fuzzy C means clustering by computing an interval of primary memberships for a pattern with two fuzzifiers m_1 and m_2 more exactly. We define $I_k = \{i | 1 \leq i \leq C, d_{ik} = 0\}$ in which $k = \overline{1, N}$ and d_{ik} is the Euclidean distance between two patterns in M-dimensions space.

$$d_{ik} = d(x - k - v_i) = \| x_k - v_i \| = \left[\sum_{j=1}^{d} (x_{kj} - vij) \right]^{1/2}$$

In case of $I_k = \emptyset$, $\overline{u}_{ik}$ and $\underline{u}_{ik}$ are determined as follows:

$$\overline{u}_{ik} = \begin{cases} \dfrac{1}{\sum\limits_{j=1}^{C} \left(\dfrac{d_{ik}}{d_{jk}} \right)^{2/(m_1-1)}} & \textit{if } \dfrac{1}{\sum\limits_{j=1}^{C} (d_{ik}/d_{jk})} < \dfrac{1}{C} \\ \dfrac{1}{\sum\limits_{j=1}^{C} \left(\dfrac{d_{ik}}{d_{jk}} \right)^{2/(m_2-1)}} & \textit{if } \dfrac{1}{\sum\limits_{j=1}^{C} (d_{ik}/d_{jk})} \geq \dfrac{1}{C} \end{cases} \tag{23}$$

$$\underline{u}_{ik} = \begin{cases} \dfrac{1}{\sum\limits_{j=1}^{C} \left(\dfrac{d_{ik}}{d_{jk}} \right)^{2/(m_1-1)}} & \textit{if } \dfrac{1}{\sum\limits_{j=1}^{C} (d_{ik}/d_{jk})} \geq \dfrac{1}{C} \\ \dfrac{1}{\sum\limits_{j=1}^{C} \left(\dfrac{d_{ik}}{d_{jk}} \right)^{2/(m_2-1)}} & \textit{if } \dfrac{1}{\sum\limits_{j=1}^{C} (d_{ik}/d_{jk})} < \dfrac{1}{C} \end{cases} \tag{24}$$

Otherwise, if $I_k \neq \emptyset$, $\overline{u}_{ik}$ and $\underline{u}_{ik}$ are determined as follows:

$$\overline{u}_{ik} = \begin{cases} 0 & \textit{if } i \notin I_k \\ \sum\limits_{i \in I_k} \overline{u}_{ik} = 1 & \textit{if } i \in I_k \end{cases} \tag{25}$$

$$\underline{u}_{ik} = \begin{cases} 0 & \textit{if } i \notin I_k \\ \sum\limits_{i \in I_k} \underline{u}_{ik} = 1 & \textit{if } i \in I_k \end{cases} \tag{26}$$

in which $i = \overline{1, C}$, $k = \overline{1, N}$.

In FCM algorithms, we usually have to face a problem which is how to initiate matrix centroid V, because initialization of matrix V can cause effect on results of clustering. Hence, we

need a method to initiate matrix centroid V to make FCM algorithms stable and effect. Next, we represent summary of a algorithm to initiate matrix centroid V base on density of patterns
Initialization centroid

- Step 1: Compute
  $\overline{z}_i = \frac{1}{N}\sum_{j=1}^{N} x_{ji}$ and $s_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(x_{ji}-\overline{z}_i)^2}$.
  With $i = 1, 2, ..., M$.
  Find $r = \min_{1<i<M} s_i$.
- Step 2: Compute density D_i of pattern x_i.

$$D_i = \sum_{j=1}^{N} T(r - \|x_j - x_i\|) \tag{27}$$

  in which $u_{jl} = \begin{cases} 1 & \text{if } z \geq 0 \\ 0 & otherwise \end{cases}$

- Step 3: Find pattern x_i with $D_i = max_{1\leq j\leq N} D_j$
  $V_u = V_u \cup x_i$
- Step 4: Compute $CC = \{x_j | r_i - \|x_i - x_j\| \geq 0\}$
  $X = X\ CC$
- Step 5: If $X = \emptyset$ then go to Step 6 else back to Step 2.
- Step 6: Ouput V_u .

We can init centroid of clusters by choose the patterns in V_u.
Algorithm: Modified interval type-2 fuzzy C means

- Input: The number of clusters C, two fuzzifiers m_1 and m_2 for objective functions J and error number ε.
- Output: C cluster of patterns to minimize objective functions (7).

Begin

- Step 1: Init Matrix centroid V: $V = [v_{ij}], V^{(0)} \in R^{M\times C}, j = 0$ following *the initialization centroid algorithm.*
- Step 2:
  - 2.1. j = j+1
  - 2.2. Compute Matrix $U^{(j)}$ by (23)-(26) and (12).
  - 2.3. Update centroid of clusters as: $V^{(j)} = \left[v_1^{(j)}, v_2^{(j)}, ..., v_c^{(j)}\right]$

  Following *Iterative algorithm for finding centroids* (11) and result of (2.2): $U^{(j)}$.

- Step 3: If $\|U^{(j+1)} - U^{(j)}\| \leq \varepsilon$ then go to *Step 4* else back to *Step 2*.
- Step 4: Output the results of clustering.

End

B. Fire Detection Algorithm

The algorithm is a combination of the method of clustering fire blob in a single image f and the checking of fire model as described above. The condition of environment is ignored in this algorithm, it will be added when necessary.
Algorithm:

- Input: A single image f.
- Output: $A = TRUE$ if f has fire, $A = FALSE$ if it has not.

Begin

- Step 0: $A = FALSE$;
- Step 1: Check whether f is taken in weak-light intensity environment by (18); if ok do step 2, otherwise do step 5;
- Step 2: Cluster f into 5 clusters C_1, C_2, C_3, C_4, C_5 by IT2FCM;
- Step 3: If the $C_i, i = 1, 2, 3, 4, 5$ are satisfied (20),(21) and (22) then do step 4; else go to step 5;
- Step 4: $A = TRUE$;
- Step 5: Return A;

End

Figure. 4: Images consist fire are taken in weak light conditions

V. Experimental results

The set of data for testing has 400 images. They were collected from Internet and some from our preparation. These images be divided into four categories: i) Set A - the images consist fire and were taken in weak light conditions; ii) Set B - the images does not contain the fire; iii) Set C - The images contain a fire-like object; and iv) Set D - set of outdoor fire images.
Summarization of experimental results with the above testing images is shown in Table 3. The results of the method

Table 3: Summary of test results

Catalog	Number Images	True Alarm	False Alarm
Set A	100	96	4
Set B	100	93	7
Set C	100	52	48
Set D	100	43	57

proposed here are reliable in images which are taken in environment with weak-light intensity , or when without fire. In situations fire-like object occurs or when the images were taken in outdoor light conditions, the result is not reliable. Some specific situations are discussed in the next section.

A. *Image with fire in the weak light condition*

With the images in the set A, as summarized in Table 3, we observe that the accuracy of results is hight, it reached 96% true alarm. Figure 5 shows some examples of the image in set A, the original images are on the left and its clustering results are on the right. First row is an image for the true alarm, clustering results of the clusters C_1 to C_5 for this image are: 0.1, 0.2, 0.2, 0.2, 0.3 and center positions are respectively: (0.0,0.0), (0.1.-0.2), (0.17 , 0.3), (0.0,0.4), (0.0,-0.24). The situations that occur error for images in the set A when the fire is too small or too large. The second image in Figure 5 is an error example, the fire is too small and clustering results of the clusters C_1 to C_5 for this image are: 0.5, 0.00, 0.1, 0.1, 0.3. The last image is another error example, the fire is too large and clustering results of the clusters C_1 to C_5 for this image are: 0.5, 0.1, 0.0, 0.0, 0.4.

B. *Image no fire or unsatisfactory condition problem*

For the images without fire or be taken in outdoor light conditions, did not check equation 20, the summarized results are shown in table 3.

The image of the set B give most valid results. Some cases of incorrect results are due to the color and the distribution of colors in the picture is consistent with the model train set out; in Figure 6, two examples satisfy this condition, the probabilities of five clusters of first image received as follow: 0.2, 0.16, 0.13, 0.21 and 0.3, and for the second image are: 0.16, 0.18, 0.16, 0.22 and 0.28.

Images containing fire-like object give true alarm such as lights, the sun i.e examples presented in Figure 6. The images of set D give unreliable results because of noise caused by the environmental light; for example, two images of set D are showed in Figure 7.

VI. Conclusions

In this paper, an approach to vision based fire detection is developed, the main idea of this proposal is modeling of fire in terms of clusters. Authors used type-2 fuzzy C mean algorithm with some modification; this improved clustering algorithm - IT2FCM - is described in section IV-A. This proposed fire model does not rely on the movement of flame so that it can work well on the situation of dynamic camera, a challenge of most previous proposals. This approach can be used for detection of fire in movies and video databases, as

Figure. 5: Images without fire

Figure. 6: Images consist a fire-like object

well as real-time detection of fire. However, as indicated in the experiment, the method proposed here is only suitable for fire detection in conditions of environment with weak light-intensity. To solve the problem as a whole we will continue testing with normal lighting conditions in future work.

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Figure. 7: Outdoor images with fire

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