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Automatic Smoke Detection Based on SLIC-DBSCAN Enhanced Convolutional Neural Network

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ABSTRACT Video flame and smoke-based fire detection usually exhibit large variations in the feature of color, texture, shapes, etc., caused by the complex environment. It is difficult to develop a robust method to detect fire based on single or multiple fire features. Since convolutional neural network (CNN) has reported state-of-the-art performance in a wide range of fields. This study present a method based on SLIC-DBSCAN and convolutional neural network to recognize flame and smoke modes connected to fire stages. First, simple linear iterative clustering (SLIC) is acted as the pre-processing step to over segment images into super-pixels. Then the use of density based spatial clustering of application with noise (DBSCAN) gathered the similar super-pixels into several clusters, which in turn provide better smoke detection accuracy by using CNN. Comparison studies are performed to base on smoke image from publicly available data and self-collected data. The experimental results demonstrated the improved smoke detection capabilities by the present method.

INDEX TERMS Smoke detection, SLIC, DBSCAN, convolutional neural network, super-pixel segmentation.

I. INTRODUCTION

Fire in living environment will lead to life, property and economic losses. Generally, forest fires, civil infrastructure and industrial fires are the main fire losses to take several decades to repair. Thus, it is essential to accurately and timely detect fire [1].

Point sensors [2]–[5] are the most commonly used fire sensing techniques for monitoring heat, gas, flame, smoke and some other important fire characteristics. In heat sensing, Chiang and Chang [6] developed a device to measure the fire stages by monitoring the temperature difference between the wall surfaces on inside and outside. Wang *et al.* [7] investigated the near-field and far-field temperature sensor array to detect fire stages. Jevti and Blagojevi [8] employed electrical and sheathed thermocouple type heat sensors to monitor wire resistance and surface temperature in associate with fire stages. For the applications of gas sensors, Liu *et al.* [9] gave a summary for gas sensing technologies by detecting the sensor output variation of the semiconductor, catalytic bead, photoionization, infrared, electrochemical, optical, acoustic, gas chromatograph, and calorimetric. Using flame sensing, both characteristics of radiation and chromatic properties are employed to form nonvisual and visual flame sensing techniques, respectively [10], [11]. Take smoke as physical quantity, there are also nonvisual (using pyrolysis, smouldering, and flaming) and visual (using cameras to capture smoke movement) smoke sensing techniques to detect fire stages [12], [13]. Generally, the fire sensing system is to detect early fire with less false positives. However, as feature based methods, the present commonly used point sensors result in high false positives for the signal processing techniques under sophisticated fire environment.

Compared to point sensors, image-based fire detection could effectively reduce interference of the outside environment. At the beginning of a fire breakout, smoke

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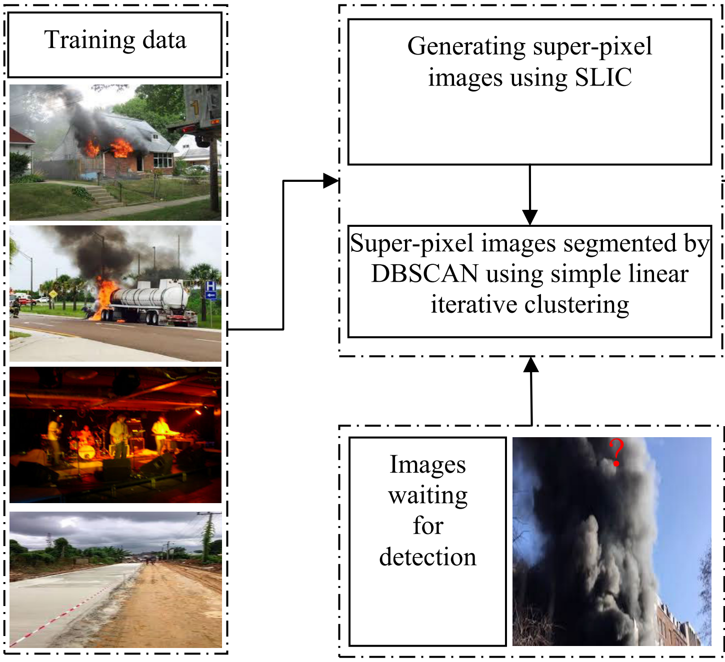


FIGURE 1. **Flowchart of the automatic smoke detection method.**

provides more timely potential information compared with fire flames. Therefore, effective smoke detection plays an important role in fire detection. Automatic detection methods are largely based on machine learning algorithms, with one pipeline using manual extracted features to train classifiers such as support vector machine [14], random forest [15], etc. However, most existing studies on automatic smoke detection train models using solo type smoke or flame frames from smoke or fire videos. It is often difficult to track more complicated smoke situations. Besides, most smoke detection algorithms only consider smoke frame or images in an ideal background without too much disturbances. Image segmentation is one of the key techniques in image processing, which has great significance to computer vision tasks. In fact, image segmentation has been extensively studied in visual detection tasks, such as SAR image segmentation, medical imaging process, UAV imagery analysis, etc. Zhao *et al.* combined super-pixel segmentation and image regression to detect changes in synthetic aperture radar (SAR) images [16]. Kesav and Rajini utilized fuzzy C-means (FCM) for brain magnetic resonance (MR) image segmentation, and then extract texture feature from the segmented images to automatic detect brain tumors [17]. Fuzzy C-means clustering was used to segment pedestrian contour as the foreground objects and then passed though HOG classifier for pedestrian detection [18]. A change detection (CD) networks for hyperspectral unmanned aerial vehicle (UAV) images was constructed with fuzzy c-means clustering to select training data [19]. Smoke segmentation [20] plays an importance role in smoke and fire detection. In order to obtain spectral feature of smoke areas, Xiong and Yan proposed an early smoke detection algorithm based on simple linear iterative clustering (SLIC) and SVM [14] but the super-pixel images segmentation might mixture together to distort the recognition precision. To get features of smoke areas, Li *et al.* first segmented smoke regions by SLIC algorithm, then calculated local binary pattern Silhouettes coefficient variant (LSPSCV) based on the segmentation results for industrial smoke images [21], however the features may not robust to variable smoke scenarios. Islam *et al.* demonstrated a Gaussian mixture model (GMM) and hue-saturation-value (HSV) color segmentation for the pretreatment of flame images which could dynamic growth feature of different fire stages [22]. Sousa *et al.* explored thermal imaging data by fuzzy modeling based systems for early fire detection [23]. Ajith and Martinez exploited motion information by Markov random field for fire video frames [24].

With the rapid development of artificial intelligent (AI) models [25], many researches applied AI models to detect abnormal conditions for mechanical and civil engineering [26]–[31] as well as fire detection domain [4], [32]–[38]. Recently, Yuan *et al.* proposed a smoke density estimation network. In order to encoding abundant semantic information, a stacked convolutional encoder-decoder structure was designed to estimate smoke density from flame images and real videos [32]. Muhammad *et al.* utilized an energy-friendly and computationally efficient CNN architecture for fire detection, localization, and semantic understanding of the scene of the fire [4]. Xu *et al.* combined the pixel-level and object-level salient convolutional neural networks to extract the informative smoke saliency map using video smoke sequence [33]. Faster region-based

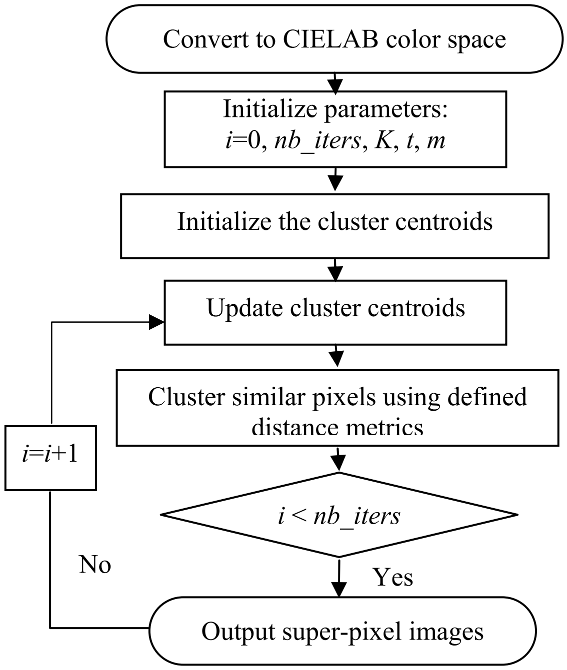


FIGURE 2. Flowchart of the SLIC.

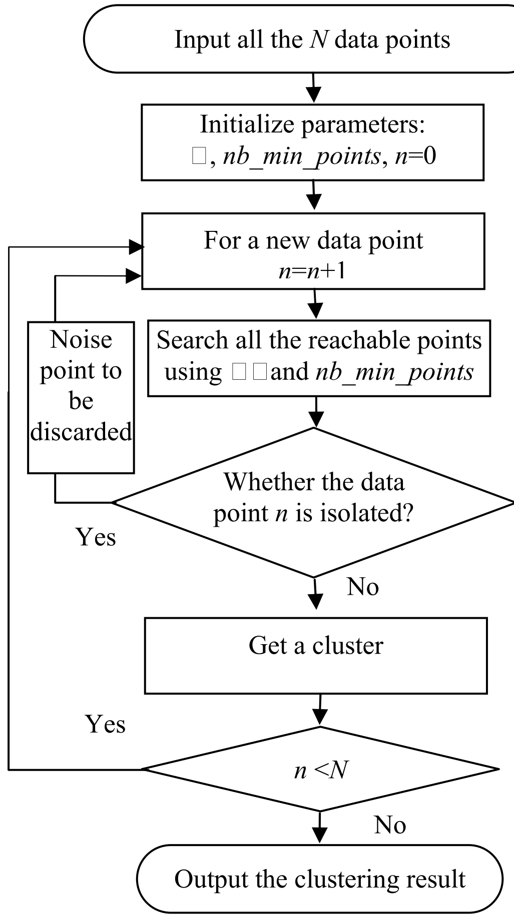


FIGURE 3. Flowchart of the DBSCAN.

convolutional neural network (CNN) and long short-term memory (LSTM) are employed to detect the suspected regions of fire (SRoFs) and classify whether there is a fire or not in a short-term period [34]. Meanwhile, CNN was extended to the fire detection process using generic object detection methods [35]. Gagliardi and Saponara. [36] proposed a video-based smoke detection technique by the combination of Kalman estimator, color analysis, image segmentation, blob labeling, geometrical features analysis, and M of N decisor for early warning in ant-fire surveillance systems. Park and Ko [15] developed a bag-of-features (BoF) histogram to generate a random forest classifier for the fast and high classification performance of the tabular features to verify fire candidates. For the real-time fire detection from the video surveillance, the complementary information of color, shape and motion were employed to classify fire stages using a bag-of-words approach [37]. In contrast to the traditional AI model, deep learning developed from artificial neural networks (ANNs) have deep architectures equipped with strong feature learning abilities [26], [29].

Most of the existing studies regarding smoke image detection or smoke video detection receive inconsistent results due to the complex backgrounds of different smoke explosion scenarios. Even though CNNs show great talent in learning representative features for smoke images, it still suffers from the above challenge. Image segmentation [22]–[24] provides an ideal way solving smoke images with complex background interference which attracts lots of attentions, especially color image segmentation [38]. For example, SLIC shows advantages in generating sub-images that have good boundary compliance [20], [21]. And, density based spatial clustering of application with noise (DBSCAN) [39], [40] perform well in grouping sub-images which belongs to the same clusters.

Therefore, a novel smoke detection method is proposed by integrating SLIC-DBSCAN with convolutional neural networks, which consists of the complex background interference splitter and a robust smoke feature extractor. The smoke images with complex backgrounds are first segmented and reconstructed using SLIC- DBSCAN. Then the candidate pure smoke images are trained with convolutional neural network for feature extraction and classification. Results of the experiment demonstrate the present method is able to classify the smoke images with improved performance which makes it suitable for the use in smoke detection.

The remainder of this paper is as follows: Section II describes the implementation details of the present method. Experimental investigations and comparisons are given in Section III. Conclusion remarks are in Section IV.

II. AUTOMATIC SMOKE DETECTION BASED ON FCM-CNN

A. AUTOMATIC SMOKE DETECTION METHOD

In light of the strong feature learning ability of CNN, this paper proposed a SLIC- DBSCAN based CNN to automatically detect smokes using images with complex backgrounds.

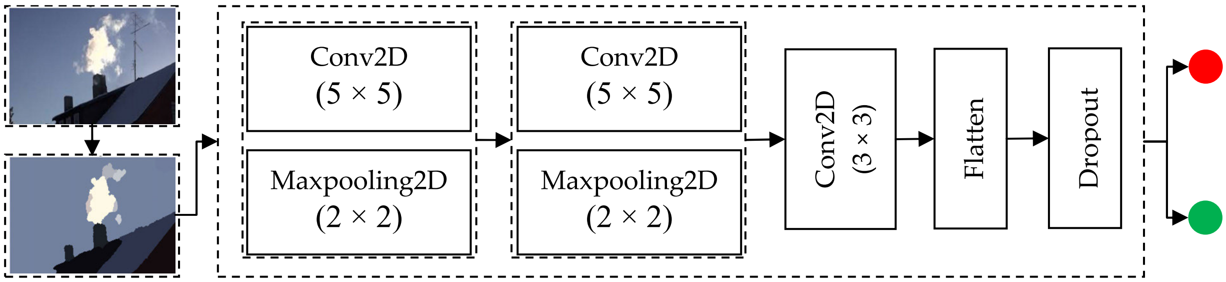


FIGURE 4. **The CNN architecture.**

(a) Smoke images

(b) Non-smoke images

(c) Fire images

FIGURE 5. **Images from the two cases.**

The combination of SLIC- DBSCAN is employed to deal with smoke images with complex backgrounds. To address the smoke/fire and non-smoke features matching alarm and normal situations, a CNN model is then applied to automatically learn smoke/fire and non-smoke features from the resize maps.

The flow chart of the automatic smoke detection workflow is illustrated in Fig. 1. The general procedures are summarized:

Step 1: First, predefine the smoke/fire and non-smoke pattern from 1 to 2, which is the prerequisite of the next labelling work for collected samples.

Step 2: The raw images are collected from the real-world situations under different fault patterns by cameras.

Step 3: The collected raw images combined with CIELAB color space are segmented using SLIC to generating super-pixel images with spectral feature of smoke areas.

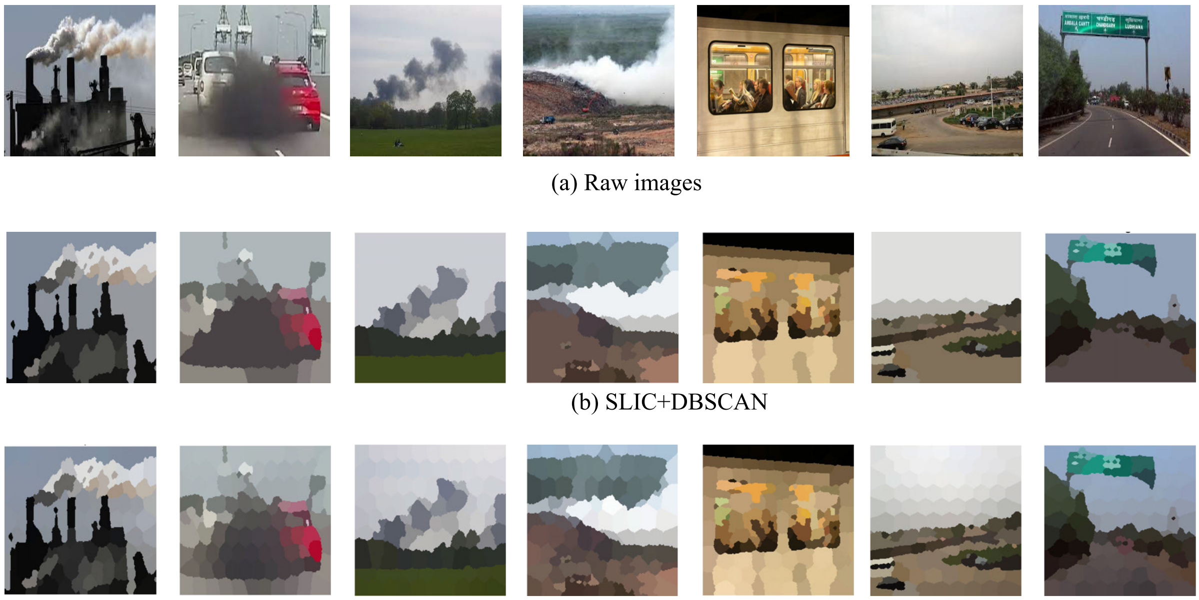
Step 4: The super-pixel images are further segmented by DBSCAN to three cluster maps, i.e., background, candidate smoke/fire area and edges.

Step 5: The CNN model is trained hierarchically by alternate convolution and subsampling operations using the training sample set by resizing the obtained cluster maps).

Step 6: The testing sample set (images waiting for detection) is treated as unknown images to recognize smoke/fire and non-smoke images.

B. SIMPLE LINEAR ITERATIVE CLUSTERING

Simple linear iterative clustering: SLIC [41] is among the most popular super-pixel generation clustering algorithm, and has been used in many image segmentation tasks. In the present method, SLIC worked with raw smoke images. Fig.2 shows the core idea: It takes the CIELAB color space [42] of the raw images into consideration and clusters the pixels to get similar areas, which finally finish the super-pixel based image segmentation. In the CIELAB color space, the image can be represented by a 5-element feature vector $V = [l, a, b, x, y]$, where $[l, a, b]$ keeps the colour information and $[x, y]$ preserves pixel position information. Therefore, the SLIC takes into account both the similarity in



(a) Raw images

(b) SLIC+DBSCAN

(c) SLIC

FIGURE 6. Segmentation results using slic+dbscan and slic in case 1.

color and position. Suppose there are N pixels in an image, the number of super-pixels is set to be K, then the area of a super-pixel is N/K. For a grid region area with N/K pixels, randomly choose a pixel as the initial cluster centroid C_k of this area. Then calculate the pixel gradient in the nearby $t \times t$ area (t usually takes 3). The pixel with the smallest gradient is the new cluster centroid. Search similar pixels based on $2\sqrt{N/K} \times 2\sqrt{N/K}$ neighbours. Then continuously iterates the feature vector until the result converges. To find the similar pixels in CIELAB color space, the distance metrics are defined as

$$d_{lab} = \sqrt{(l_k - l_p)^2 + (a_k - a_p)^2 + (b_k - b_p)^2} \quad (1)$$

$$d_{xy} = \sqrt{(x_k - x_p)^2 + (y_k - y_p)^2} \quad (2)$$

$$D_p = d_{lab} + \frac{m}{d_c} d_{xy} \quad (3)$$

in which d_{lab} is the colour distance between pixel p and cluster centroid C_k, d_{xy} is the position distance between pixel p and cluster centroid C_k, D_p is a weighted distance of the both two, m is a hyper-parameter of SLIC, d_c denotes distance between cluster centroids.

C. DENSITY BASED SPATIAL CLUSTERING OF APPLICATION WITH NOISE

DBSCAN [38] works with two predefined parameters, a positive number ε and a natural number *nb_min_points*. The core idea is as follows: For a data point, first check if there are more than *nb_min_points* points (including the point) within the distance of ε-ball from it, if so, all the reachable points are considered to be part of a cluster. Then check all the reachable points to see if they have more than *nb_min_points* within the distance of ε-ball, if so, expanded the cluster. If a data point (including the point and its reachable data points) has neighbors less than *nb_min_points* within its ε-ball, then it's considered as a noise point. Iterate the two steps for all the data points to finish clustering. The algorithm is shown in Fig. 3.

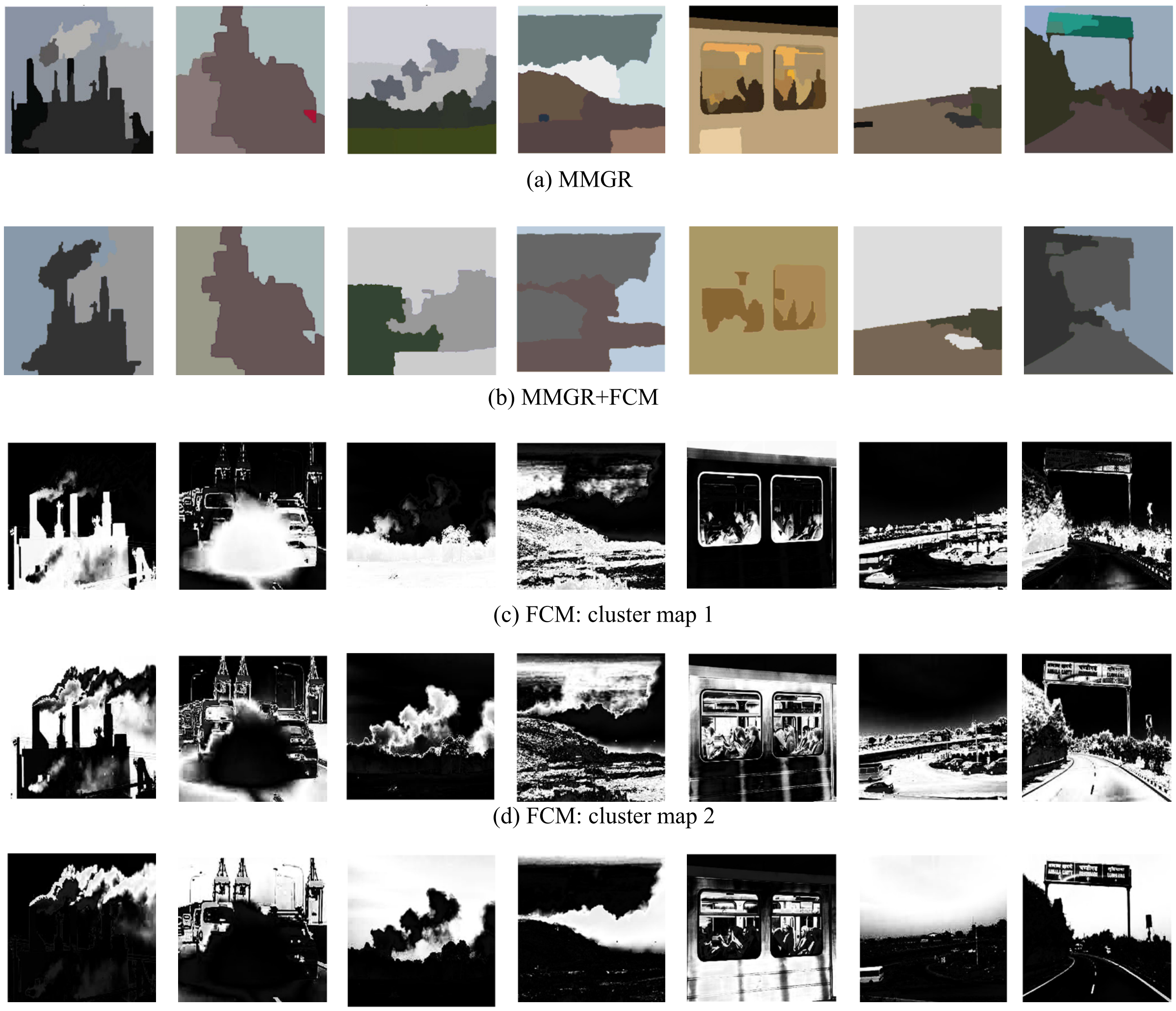
D. CONVOLUTIONAL NEURAL NETWORK

CNN architecture consists convolutional layers, maxpooling layers, a flatten layer and a dropout layer. The first layer consists of a convolutional layer with 6 filters of size 5×5 with relu activation function, maximum pooling with stride size 2×2. The second layer consists of a convolutional layer with 12 filters of size 5×5 with rectified linear units (ReLU) activation function, maximum pooling with filters size 2×2. The third contains a convolutional layer with 24 filters of size 3×3 with ReLU activation function. The fourth layer is a flatten layer and with the dropout ratio of 0.7. The final layer is output layer with sigmoid function to give results. Fig. 4 shows the architecture of the mentioned CNN architecture.

III. EXPERIMENTAL INVESTIGATIONS

A. SMOKE DETECTION DATASET

Case studies are conducted to validate the performance of the present method. The case uses smoke images from public smoke dataset, which is collected by DeepQuest AI [43]. The public smoke dataset consists of 3000 images including 1000 fire images, 1000 smoke images and 1000 non-smoke images). As we all know, data imbalance has great impact to model training. Therefore, to avoid the influence of the problem, here we only choose the smoke images and non-smoke images for our smoke detection task. Parts of the images from smoke and non-smoke categories are shown



(a) MMGR

(b) MMGR+FCM

(c) FCM: cluster map 1

(d) FCM: cluster map 2

(e) FCM: cluster map 3

FIGURE 7. **Results of other segmentation methods in case 1.**

in Figs 5 (a) and (b). The smoke images are recorded by day and by night, from buildings and from vehicles. The non-smoke images contain clouds, snows and sun light which are easily confused features to smokes. Besides, these images are various in smoke colors, background, illumination and so on.

The evaluation metric used for the present method are list below.

To evaluate the performance of the present method, the detection rate, false alarm rate, and average accuracy rate *(AAR)* are adopted as the evaluation criteria. Given the smoke dataset of positives (smoke image) and negatives (non-smoke image), true positive *(TP)*, true negative *(TN)*, false positive *(FP)*, and false negative *(FN)* are calculated from the binary classifier. In fact, detection rate is the true positive rate *(TPR)*, and false alarm rate is the false positive rate *(FPR)*.

$$TPR = \frac{TP}{(TP + FN)} \tag{4}$$

$$FPR = \frac{FP}{(FP + TN)} \tag{5}$$

$$AAR = \frac{TP + TN}{(TP + TN + FP + FN)} \tag{6}$$

in which TP is the number of smoke image classified as smoke, TN is the number of non-smoke image classified as non-smoke, FN is the number of non-smoke image classified as smoke, and FP is the number of smoke image classified as non-smoke.

B. RESULT AND DISCUSSION

1) CASE 1: SMOKE AND NON-SMOKE IMAGES

The smoke and non-smoke images are divided into training set and testing set. The testing set takes 0.2 ratio of the whole dataset. The validation set takes 0.33 ratio of the training set. The optimizer is Adam and training epochs are setting to 100. Comparisons of different segmentation results for smoke detection are given, as shown in Fig 6 and Fig 7. Fig. 6 shows

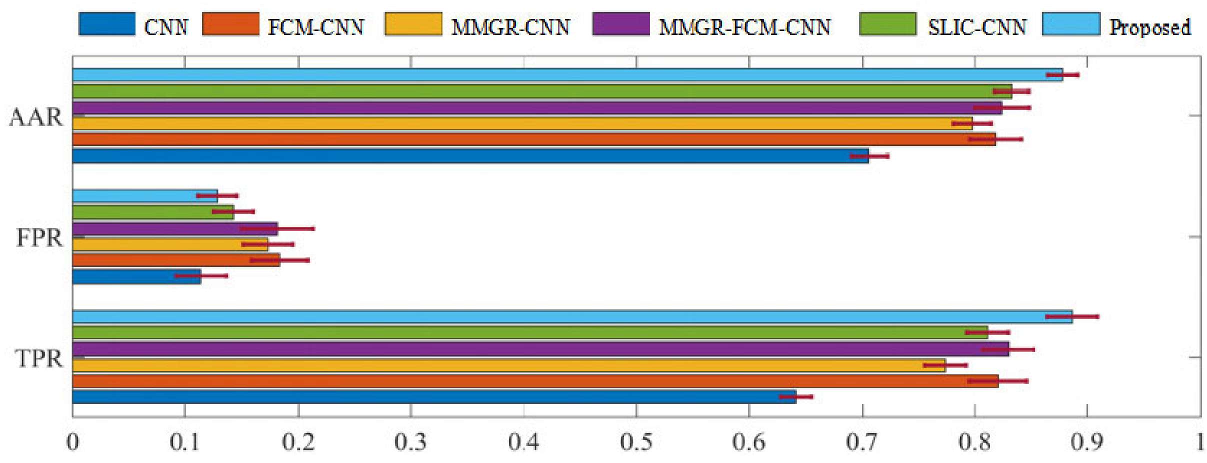


FIGURE 8. Performance metrics of comparison study for case 1.

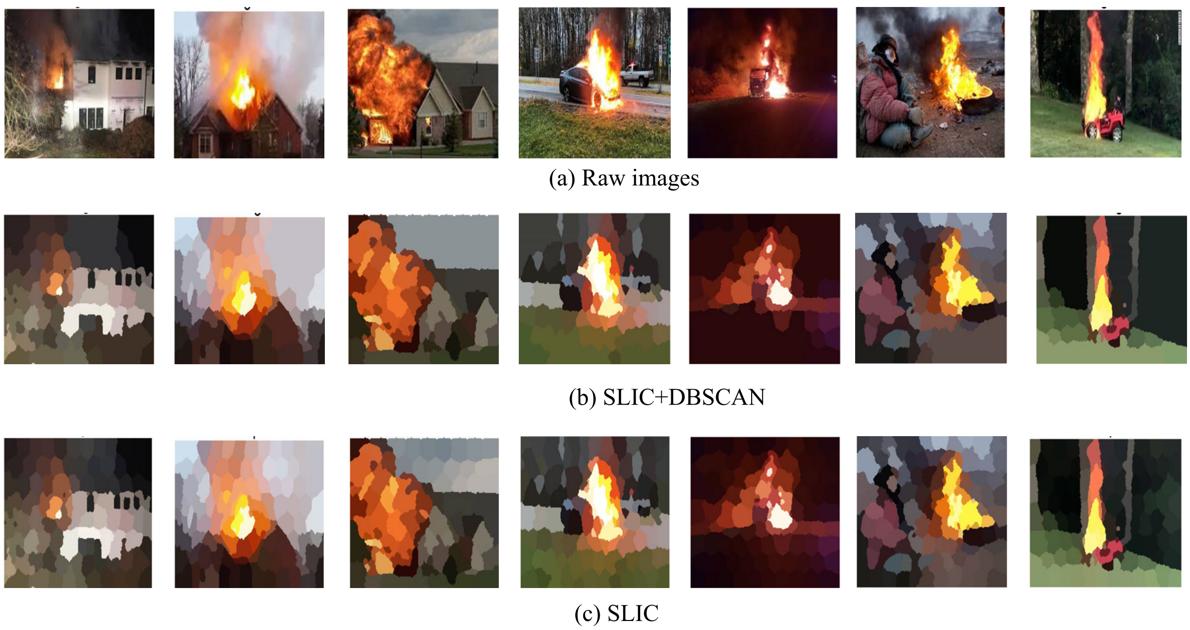


FIGURE 9. Segmentation results using slic+dbscan and slic in case 2.

the segmentation results of SLIC-DBSCAN and SLIC. It can be seen that by using SLIC-DBSCAN rather than SLIC alone, smoke regions with similar features are clustered together, and other irrelevant features are basically eliminated, which means this really helpful for smoke detection with complex background. Unlike many other image segmentation methods work with gray scale image (such as the results of FCM in Fig. 7) that may loss some useful information of the color image, SLIC-DBSCAN could directly cluster sub-images (super-pixels obtained from SLIC) from the color image.

Fig. 7 shows the segmentation results of comparison methods using fuzzy c-means (FCM), multiscale morphological gradient reconstruction (MMGR), and the combination of MMGR and FCM (MMGR+FCM) [44]. The reason we choose these methods for comparisons is that they are commonly used for image segmentation. We can see that compared with FCM, MMGR and MMGR+FCM, SLIC-DBSCAN could better remain import features of the raw images.

TABLE 1. Precision, recall and F1-Score for Case 1.

Pattern	Proposed (%)			CNN (%)		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Smoke	92.47	86.00	89.12	64.08	84.50	72.88
Non-smoke	86.92	93.00	89.86	84.48	56.00	67.35

Table 1 reports the precision, recall and f1-score in Case 1 of one trail. We can see that the precision, Recall and F1-Score of the proposed method for smoke and non-smoke are 92.47% and 86.92%, 86% and 93%, 89.12% and 89.86%, respectively. By comparing with CNN alone, the superior of the present method is obviously.

Fig. 8 shows the average results of the above comparison studies among 20 trails. The metric values of TPR, FPR

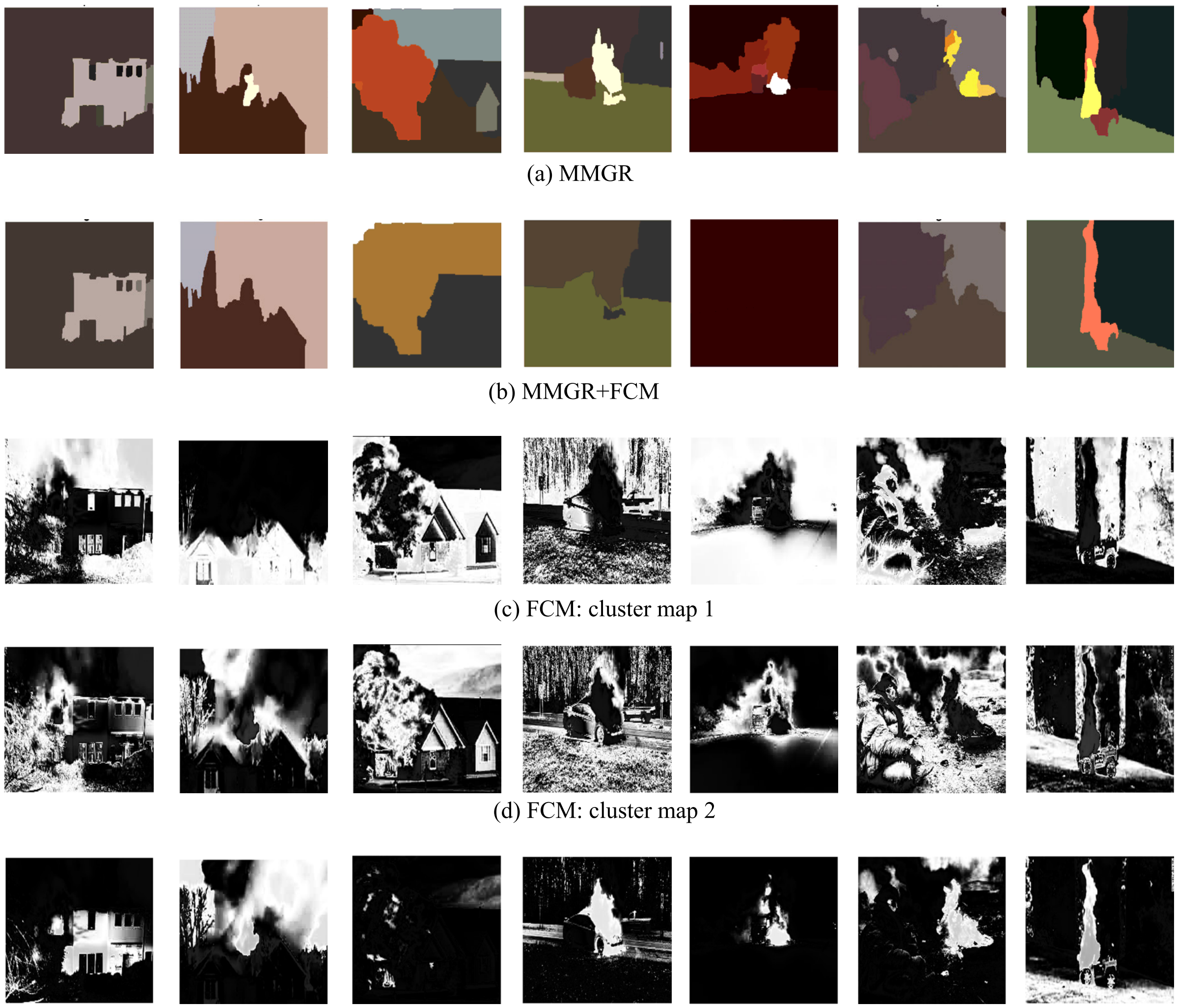

(a) MMGR
(b) MMGR+FCM
(c) FCM: cluster map 1
(d) FCM: cluster map 2
(e) FCM: cluster map 3

FIGURE 10. Results of other segmentation methods in Case 2.

TABLE 2. Comparisons with other deep methods.

Pattern	ResNet-50 (%)			Xception (%)		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Smoke	68.15	84.50	75.45	83.84	83.00	83.42
Non-smoke	79.61	60.50	68.78	83.71	84.00	83.58

and AAR of the proposed method are 88.69%, 12.85%, 87.85%, respectively. The metric values of TPR, FPR and AAR of CNN, FCM-CNN, MMGR-CNN, MMGR-FCM-CNN, SLIC -CNN are respectively: 64.13%, 11.37% and 70.66%; 82.03%, 18.33% and 81.81%; 77.4%, 17.30% and 79.78%; 82.98%, 18.10% and 82.38%; 81.12%, 14.27% and 83.24%. Compared with the five commonly used methods, it can be seen that both the TPR and AAR values of the present method are the highest ones. However, the FPR value of the present method is slight lower than those of FCM-CNN, MMGR-CNN, MMGR-FCM-CNN and SLIC-CNN but higher than CNN alone. The evaluation metrics are calculated by Eqs. (4) to (6).

To compare with the state-of-the-art deep learning methods, we conduct experiments on ResNet-50 and Xception. Table 2 gives the results, we can see in the case, the proposed method shows a bit improved performance.

2) CASE 2: FIRE AND NON-FIRE IMAGES

In case 2, we consider the fire and non-smoke images. Fig 9 shows the segmentation results of SLIC-DBSCAN and SLIC. It can be seen that the advantage of using SLIC-DBSCAN is obviously. The similar smoke regions are merged into same clusters, and other irrelevant features that do nothing with smoke area are naturally eliminated.

The corresponding classification precisions are shown in Table 3. Among one trail, the precision, recall and F1-score of the proposed method are 96.95% and 95.57%, 95.5% and 97%, 96.22% and 96.28%, respectively. By comparison with the usage of CNN alone, we can see that the proposed method shows a bit improved performance.

The image segmentation results for Case 2 using MMGR, MMGR+FCM, and FCM are shown in Fig 10.

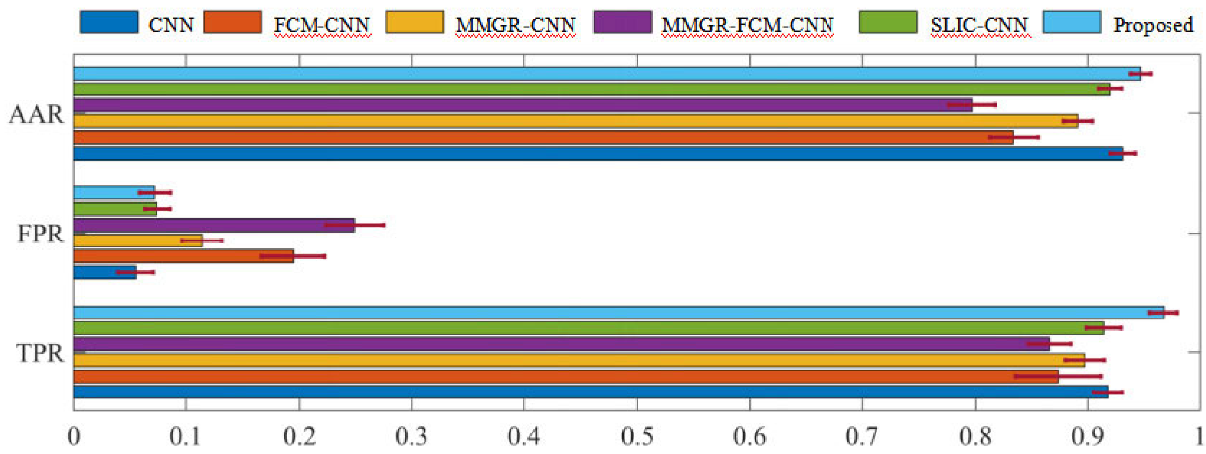


FIGURE 11. Performance metrics of comparison study for Case 2.

TABLE 3. Precision, recall and F1-Score for Case 2.

Pattern	Proposed (%)			CNN (%)		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Fire	96.95	95.50	96.22	92.46	92.00	92.23
Non-smoke	95.57	97.00	96.28	92.04	92.50	92.27

TABLE 4. Comparisons with other deep methods.

Pattern	ResNet-50 (%)			Xception (%)		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Smoke	88.69	98.00	93.11	98.43	94.00	96.16
Non-smoke	97.77	87.50	92.35	94.26	98.50	96.33

We also make comparison investigations. Fig 11 shows the corresponding results. Compared with the five methods, the same results can also be obtained. The values for TPR, FPR and AAR of the proposed method are 96.70%, 7.21%, 94.64%, respectively. The metric values of TPR, FPR and AAR of CNN, FCM-CNN, MMGR-CNN, MMGR-FCM-CNN, SLIC-CNN are respectively: 91.78%, 5.48% and 93.09%; 87.39%, 19.46% and 83.45%; 89.73%, 11.40% and 89.13%; 86.64%, 24.97% and 79.68%; 91.40%, 7.42% and 91.96%.

Table 4 gives the results of ResNet-50 and Xception of Case 2. In the case, Xception shows comparative results with the proposed method. We must note that, we proposed CNN as a feature extractor here followed by SLIC-DBSCAN, the architecture of CNN is not our focus. Therefore, we only choose a simple CNN in Fig. 3. The effectiveness of the proposed method can be reflected by Table 3 and Fig. 11.

IV. CONCLUSION

In this paper, a hybrid of SLIC-DBSCAN and CNN model is proposed to recognize fire and smoke modes connected to fire images to generate an automatic smoke detection scheme. SLIC has the strong ability to obtain spectral feature of smoke areas represented by super-pixel images but not always work well for the mixture of super-pixel images to distort the recognition precision. As a density based clustering method, DBSCAN can group the unrecognizable area to one according to the number other data points nearby in that cluster. However, DBSCAN parameters are difficult to be chosen for raw images. Based on the above analysis, the combination of SLIC with DBSCAN might be a good choice to deal well with smoke images that have complex backgrounds. Advantages of CNN model for its strong ability in fire and smoke image feature learning and pattern recognition is utilized to achieve fire situation detection.

Experimental investigations are performed by a commonly used fire detection dataset. The metric values of TPR, FPR and AAR of CNN, FCM-CNN, MMGR-CNN, MMGR-FCM-CNN, SLIC-CNN are compared. Both the TPR and AAR values of the present method are the highest ones. However, the FPR value of the present method is slight lower than those of FCM-CNN, MMGR-CNN, MMGR-FCM-CNN and SLIC -CNN but higher than CNN alone. In real-world applications, the TPR and AAR values are the main indexes to evaluate a fire alarm algorithm. The slight lower of FPR value means the sensitive of the present method is relative higher need to be further improvement.

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