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A Review of Smoke Detection Techniques Using Deep Learning and Image Processing: Challenges and Future Directions

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Abstract: Traditional smoke detection methods, relying on sensors for temperature, smoke, and light changes, face limitations in large or outdoor environments due to their dependency on proximity to combustion by-products. While early image processing techniques improved detection accuracy for complex spaces, they were constrained by manually set thresholds and shallow feature extraction, resulting in high false detection rates and poor generalization. The advent of deep learning has transformed smoke detection, allowing for automatic feature extraction and improved accuracy. This paper reviews the progress of deep learning techniques applied to smoke detection, highlighting convolutional neural networks (CNNs) and their effectiveness in capturing static smoke features. Despite these advances, challenges remain in detecting dynamic smoke features, especially in complex environments. Future research directions include the simultaneous extraction of smoke color and texture features, the use of multi-scale optical flow and velocity distortion to track smoke dynamics, and the integration of CNNs with support vector machine classifiers to enhance detection accuracy in diverse conditions.

Keywords: Deep Learning; Smoke Image Recognition; Convolutional Neural Networks; Support Vector Machines.

1. Introduction

The majority of traditional smoke detectors use smoke, temperature, light and composite detectors, which rely on detecting the by-products of combustion (smoke particles, temperature changes, etc.) to detect smoke, so they can only be used quickly and effectively in close proximity to the flame and smoke source, and are less reliable for large spaces or outdoor locations. In the 1940s, traditional image processing techniques emerged and some scholars worked to apply them to smoke detection, which is highly accurate, flexible and still effective in detecting smoke in large spaces and complex building structures. However, the smoke discrimination criterion of this research method relies on artificially set thresholds and is not universally applicable[1] The algorithm that extracts only shallow features has low accuracy, high false detection rate, and weak generalisation to new scenes and unexpected conditions.

In recent years, the rapid development of deep learning algorithms, using deep learning techniques, the design of self-learning classifier, from a deeper level of automatic mining features and analysis, with high accuracy, low cost, fast and other advantages, is widely used in the field of license plate recognition, face recognition, has become a new idea in the field of fire video image detection.[1] . Therefore, the application of deep learning in smoke recognition is an important topic for continuous research now and in the future. It is proposed to investigate and review the existing research in this field, and make an attempt to promote the progress of research in this area. Firstly, the concept of deep learning is explained and the essence of deep learning is briefly described, followed by a detailed description of the algorithms commonly used for smoke detection and their performance in recent years, and finally the development trend of smoke detection is summarised.

2. Deep Learning Overview

Deep learning (DEEP LEARNING)[3] is a branch of machine learning that is based on artificial neural network It is an algorithm that uses artificial neural networks as the architecture for learning representations of data. Several deep learning frameworks, such as deep neural networks, convolutional neural networks and deep confidence networks and recurrent neural networks, have been used in computer vision The deep learning framework has been applied in the fields of computer vision, speech recognition, natural language processing, audio recognition and bioinformatics with excellent results. Commonly used algorithms in the field of deep learning include deep confidence networks (DBN), convolutional neural networks (CNN), recurrent neural networks (RNN) and generative adversarial networks.

Deep learning is essentially[4] is the construction of a machine learning architecture model containing multiple hidden layers, which is trained by large-scale data to obtain a large amount of more representative feature information. This leads to the classification and prediction of samples and improves the accuracy of classification and prediction. This process is achieved by means of deep learning models for the purpose of feature learning. The differences between deep learning models and traditional shallow learning models are: (1) deep learning model structures contain more layers, containing hidden nodes usually in more than 5 layers, sometimes even containing up to 10 or more layers of hidden nodes; (2) the importance of feature learning for deep models is explicitly emphasised, i.e. through layer-by-layer feature extraction, the features of data samples in the original space are transformed to a new feature space to represent the initial data, which makes the classification or prediction problem easier to implement. Compared to manually designed feature extraction methods, the data features obtained using deep model learning are more representative of the rich inherent information in big data. Deep learning is also widely used in the field of fire image recognition, especially in smoke recognition, and commonly used are convolutional neural networks, support vector machines, Gaussian mixture models, VGG-16, random forests, etc.

3. Deep Learning Models in Smoke Recognition

3.1 Convolutional Neural Networks

Convolutional neural networks are feed-forward neural networks with artificial neurons that respond to a portion of the surrounding units in the coverage area and excel for large image processing. 2012, KRIZHEVSKY A et al.[5] achieved the world's best result of the year on the famous ImageNet image dataset using a deeper CNN, reducing the recognition error rate from 26% to 15% and substantially improving the accuracy of large-scale image recognition.

In the application of convolutional neural networks in the field of smoke detection, some scholars will improve the convolutional neural networks to make the application better in view of the problems of slow learning speed, easy to fall into local minima, and no corresponding theoretical guidance on the selection of the number of layers and neurons of the network.

2015 Caixia Wang[6] Applying 3D convolution to neural network model training. Continuous image sequences can be directly fed into this network model. After experiments, it is found that the network can automatically extract more features and has better recognition effect in fire recognition of videos.

2016 Chen, Jun-Zhou[7] A cascaded convolutional neural network smoke texture recognition framework was proposed to fuse static and dynamic texture information, taking the original image as input on static texture and the optical flow sequence of the original image as input on dynamic texture, and the final experimental results showed that the method achieved better performance in both smoke recognition accuracy and false detection rate. However, it was found that the false detection rate of smoke was higher after recognition by static texture.

2017 Xingkun Zhang[8] A multi-layer hidden layer design was added to the convolutional neural network structure. After experiments, it was found that if the network was trained using better and more heavily targeted data, then a network model with better generalisation performance could be obtained for fire detection and recognition.

2018 Fengwei Gao[9] et al. used CNN models to identify smoke images and then combined them with dynamic texture features of smoke to determine whether they were smoke or not; this method reduced the impact of changes in external lighting and smoke concentration on the model recognition. This method reduces the impact of changes in external illumination and smoke concentration on the model's recognition. All of these scholars focus on the texture features of smoke as the entry point for fire recognition. However, the recognition process focuses on the static texture features of smoke, but the dynamic smoke features still need to be tackled.

In 2019, Yudi Li et al.[10] transformed the traditional CNN into a batch normalized convolutional layer, which effectively solved the gradient dispersion and model overfitting problems that often occur in the training of the network, thus shortening the training time and improving the training effect as a result; in addition, the imbalance between positive and negative samples was overcome by increasing the number of training samples. In the same year, Khan et al.[11][10] proposed an energy-efficient system based on deep convolutional neural networks for early smoke detection in normal and foggy IoT environments. However, the work on detecting and localising smoke needs to be refined to facilitate the extraction of detailed information such as smoke area, growth rate, distance from the camera, etc.

3.2 Support Vector Machines

Support vector machines are a class of generalised linear classifiers that perform binary classification of data in a supervised learning fashion, with a decision boundary that is a maximum margin hyperplane solved for the learned samples, allowing the problem to be reduced to one of solving a convex quadratic programming problem. Support vector machines, compared to logistic regression and neural networks, offer a clearer and more powerful way of learning complex non-linear equations. In the fields of portrait recognition, text classification Many scholars have used SVMs in conjunction with sensors for dynamic texture characterisation of smoke in the field of fire image recognition. However, as the basic model is to find the separated hyperplane with the maximum interval in the feature space, so that the nearest sample point is as far away as possible from the hyperplane, the main purpose is classification, so smoke detection is used in conjunction with other algorithms.

2010 Zhao J et al.[12] proposed a visual sensor and support vector machine based fire detection method. A modified version of the moving region detection and fire colouring pixel method was used to detect candidate fire regions and applied to a two-class support vector machine (SVM) classifier with a radial basis function (RBF) kernel, and the final fire pixel validation was performed using the SVM classifier. Experimental results show that the method is more robust to noise such as smoke and subtle differences between consecutive frames than other methods.

2014 Liu, Ying et al.[13] Smoke detection algorithm based on LSA features and SVM as a new approach to solve the dynamic texture feature detection of smoke. The aim is to improve the efficiency of smoke detection while avoiding the computational effort of continuous processing of inter-frame features. The image is chunked and the wavelet texture features and colour features are extracted from the chunks, and then the latent semantic features of the whole image are obtained using latent semantic analysis. The SVM classifier is then trained based on the latent semantic features and the image labels in the training set. The algorithm is proved to be simple and feasible, and has a high detection success rate in specific scenes, but the robustness needs to be improved due to the small number of selected features.

2017Wang[14] et al. proposed a dynamic texture feature recognition method for early fire smoke based on video information by fusing multiple features of smoke. Colour features of suspicious areas were extracted based on the colour model of early smoke in RGB and HSI space. The optical flow method is used to investigate features in the direction of primary motion. Feature values for colour, background blur, contour irregularities and principal direction of motion are used to form feature vectors which are fed into a support vector machine. An artificial bee colony algorithm was used to optimise the SVM parameters. Experiments show that the method can improve the accuracy of smoke detection and can be used in outdoor environments.

2019 Uduak Umoh et al.[15] Combining sensors with support vector machine learning algorithms, support vector machine-based fire outbreak detection can solve the problem of fire management by continuously monitoring environmental changes that lead to fire outbreaks, such as temperature, smoke and fire outbreaks.

3.3 Other Smoke Detection Algorithms

In addition to the mainstream convolutional neural networks and support vector machines, other deep learning algorithms such as Gaussian mixture models, VGG-16 and random forests are also widely used for smoke recognition, mainly from texture features, colour and ambiguity, and have achieved a little scientific success.

The Gaussian mixture model was proposed in 1886, and Truc et al.[16] first used a Gaussian mixture model to extract moving regions, and then extracted features such as texture, colour and ambiguity from the detected moving regions to propose a multi-feature fusion smoke detection algorithm. The algorithm has high accuracy, but is computationally intensive, resulting in not very good real-time performance. 2006 Calderara et al.[17][17] proposed the use of Gaussian mixture model and background difference method to extract suspected smoke areas, then extract the colour and texture features of the image, and finally classify and identify smoke by Bayesian network. This method is convenient and simple, but it is only suitable for smoke recognition in simple environments, and does not work well in complex environments. 2013 Chen[18] et al. in 2013 implemented an algorithm based on Gaussian mixture model to detect forest fires. Firstly, this model was built in HSV colour space and combined with motion target detection to segment suspected areas of flames in images with forest as background. Finally, the desired goal of high recognition rate was achieved.

In 2013 Park JunOh et al.[19] proposed the use of background differencing and non-parametric colour space to detect suspected smoke patches, and built a classifier to determine the presence of smoke based on its motion characteristics. This method has the advantage of reducing smoke detection time, but also has the inevitable disadvantage of creating 'voids' in the smoke detection area and is not very effective in complex environments.

In 2017 J. Park et al.[20] proposed a fire smoke detection method based on a random forest classifier and a spatio-temporal feature package. The random forest algorithm using spatio-temporal feature packet histogram greatly improved the recognition rate and real-time performance of the fire recognition algorithm.

2019 Wei Xin et al.[21] first used a pre-trained VGG-16 model for feature extraction of forest fire smoke images, and then proposed a deep convolutional long and short-term memory network to segmentally fuse the static and dynamic features of smoke, and finally with a fully connected layer for forest fire recognition. After validation, this network resulted in a significant improvement in accuracy.

Although these algorithms do not achieve more desirable results, the advantages of faster training and higher accuracy rates offer a new approach to the exploration of smoke detection.

3.4 Deep Learning in Smoke Detection

The application of deep convolutional neural networks to video smoke detection allows for the learning of feature models with higher generalisation capabilities and deeper levels, and this work confirms that the application of deep learning techniques to smoke recognition can break through the accuracy of traditional recognition algorithms. From the above, the mainstream algorithms for smoke detection are convolutional neural networks and support vector machines; CNNs are mainly used to identify fires based on the static texture features of smoke, but cannot be solved for the dynamic texture features of smoke; SVMs are more effective as classifiers with other algorithms to detect the dynamic features of smoke; Gaussian mixture models, random forests and other algorithms are used to identify the dynamic texture features of smoke. The use of Gaussian mixture models, random forests and other algorithms to identify dynamic texture features in smoke has been effective to varying degrees. The performance of these algorithms in smoke identification is shown in Table 1 The performance of these algorithms is shown in Table 1.

Table 1. Performance of deep learning algorithms for smoke recognition

Algorithms	Application Scenarios	Advantages	Disadvantages
Convolutional neural networks	Static smoke characteristics	Automatic extraction of image features and sharing of convolutional kernels allows the network to facilitate processing of high-dimensional data.	Slow to operate and can get stuck in saddle points
Support vector machines	Dynamic smoke features	The most mature image classification tool in machine learning, enhancing the robustness and generalisation of the algorithm; requires little in terms of the internal features of the data and the size of the data volume.	SVM algorithms are difficult to implement for large training samples; difficulties in solving multi-classification problems with SVM; sensitive to missing data and sensitive to the choice of parameters and kernel functions.
Gaussian mixture model	Static smoke characteristics	Robustly overcomes the effects of light changes, shaking, etc.	It is not possible to detect large and slow moving targets completely and accurately; the pixel points of moving targets are not concentrated and only partial outlines of moving targets can be detected and the complete area of the target object cannot be extracted; it is not possible to distinguish well the background revealed area from the moving target area.
VGG-16 model	Dynamic smoke features	Simplifies the structure of convolutional neural networks.	The number of features trained is very large.
Random Forest Classifier	Dynamic smoke features	Ability to handle very high dimensional data without feature selection and adaptability to the dataset: both discrete and continuous data can be processed and the dataset does not need to be normalised.	When there are a large number of decision trees in a random forest, the space and time required for training is relatively large.
Background Difference Method	Static smoke characteristics	The algorithm is relatively simple; the influence of ambient light is somewhat overcome.	Cameras that cannot be used for sports. Difficulty in updating background images in real time.

4. Summary and Outlook

From the previous review and summary, it is clear that researchers have achieved many results at the intersection of deep learning and image recognition, however, the current research in the application of smoke recognition is still not perfect. Many scholars have worked on optimising algorithms to be able to detect smoke features more effectively and accurately, but the detection effect in complex situations at the time of application still needs to be improved.

Through this review, possible future research priorities and directions are listed in the hope of advancing research in this field.

(1) For smoke static texture feature recognition, using the mainstream convolutional neural network has higher recognition accuracy and better performance, due to the dynamic changes in smoke will lead to recognition errors, requiring the use of algorithms to meet the detection of different colours of smoke, can consider the extraction of smoke colour features and smoke texture features at the same time, set two levels of detection of smoke to increase the accuracy of recognition. The algorithm can be considered to extract both the colour features of the smoke and the texture features of the smoke, and set two levels of smoke detection to increase the accuracy of recognition.

(2) For the problem of difficult dynamic texture feature recognition, in order to obtain a universally applicable smoke detection algorithm, one could consider studying the dynamic change in smoke colour, area change combined with multi-scale optical flow calculation and velocity distortion, or combining a smoke detector to detect the change in smoke concentration and thus obtain the dynamic trend of smoke. Or use convolutional neural networks in combination with support vector machine classifiers to achieve better results.

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