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Enhancement of the Infrared Imaging Detection Model for Highway Tunnel Fires Using the AdaBoost Algorithm

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In order to effectively detect the flame in the early stage of highway tunnel fire and issue early warning, we proposed an innovative flame identification method to solve the problem of slow response speed of traditional temperature-sensing fire flame detector in large space environment such as highway tunnel. Based on the multi-feature and AdaBoost algorithm of the flame image, the static and dynamic features of the runaway flame in the image are studied, the motion foreground is extracted by the inter-pause difference algorithm, and the suspected flame area is segmented according to the color statistical model of the flame in RGB and Lab space. We further extract the eigenvalues of the first-order moment, circularity and LBP first-order moment of the H component from the suspected region to form the input vector of the AdaBoost static feature model, and construct the AdaBoost comprehensive feature model by combining the dynamic features such as the normalized eigenvalue of the beat frequency of the flame centroid and the proportion of the flame ton. In order to verify the effectiveness of the proposed method, we used the highway tunnel flame video and public video to conduct rigorous experimental tests on the trained AdaBoost static feature classifier and comprehensive feature classifier. The method achieves high-precision initial flame identification in the highway tunnel environment, with an accuracy of 97.21% and an accuracy of 98.01%. In addition, we provide statistics such as confidence intervals to support the accuracy of the report, and demonstrate a benchmark against state-of-the-art methods in the field, demonstrating that the method has significant advantages in eliminating false alarms caused by false flame interference.

Povzetek: Predstavljen je AdaBoost okvir za zgodnje odkrivanje plamenov v predorih. Razvita je barvna segmentacija (OHTA/Otsu), statične/morfološke/teksturne značilke in dinamika utripanja; izboljšave so testirane na realnih tunelskih videih.

1 Introduction

At present, the total amount and scale of highway tunnels in China have been in the leading position in the world, and the construction and management of highway tunnels have entered a period of equal emphasis [1, 2]. In the operation and management of highway tunnels, tunnel fire is the most harmful safety accident. Traditional temperature-sensitive fire flame detectors are easily affected by monitoring space area, height, dust, airflow velocity and other factors, which is not conducive to timely and effective detection of fire in the early stage of tunnel fire [3]. Image-based fire flame detection technology can overcome the limitations of traditional sensors such as limited detection distance and slow response speed [4, 5]. As long as the flame appears in the video monitoring area, the flame detection program can immediately identify and output alarm signals, and the detection is more accurate and faster. Image fire detection technology is the most effective technology to realize the early fire flame detection of highway tunnel at present.

At present, although scholars at home and abroad have proposed a variety of image-based flame detection algorithms for the early stage of fires in confined spaces such as highway tunnels, these algorithms have significant limitations [6, 7]. Although Noda et al.'s study was based on the black-and-white television monitoring equipment in the tunnel and the grayscale histogram difference was used to identify fires, the method only used grayscale images and lacked color information, resulting in limited detection accuracy [8, 9]. Although the method proposed by Han et al. uses color information to segment the candidate flame region and eliminate interference, reducing the false detection rate, some of the experimental samples are taken from the laboratory, and the difference between the color rendering index of the ambient light and the tunnel light affects the universality of the algorithm [10]. Although Chen et al. used two-dimensional projection technology and suspected fire probability model to improve the robustness to the change of ambient light in tunnels, the algorithm is complex and time-consuming, which is not conducive to real-time detection [11]. Although Wong et al. experimented with flame detection in large spaces such as tunnels, the limited flame samples and identification features limited the scope of its application [12]. Although the detection ability of Habiboglu et al.'s method is better than that of the previous method, when the flame is small and far away from the camera, the detection effect is not satisfactory because the flame flicker is not significant [13]. Although Dimitropoulos et al. constructed a complex flame model, the dynamic texture analysis process based on linear dynamic systems was too time-consuming and not conducive to practical application [14]. Although the research of Wang et al. has improved the accuracy of flame recognition, the application of the algorithm is limited due to the limited flame and interference samples in highway tunnels, and the dynamic feature extraction is also limited [15].

Based on the in-depth study of the video library of highway tunnel flame and pseudo-flame interference samples, combined with the previous research results, this paper proposes an initial flame recognition method for highway tunnel fire based on the combination of multiple features of flame image and Ada-Boost (Adaptive Boosting) algorithm. In this method, the AdaBoost static and comprehensive feature models are constructed by using the flame color statistical model based on RGB and Lab space to segment the candidate flame regions, and extract the color, morphology and texture eigenvalues of the flame such as the H-component first-order moment, circularity, LBP first-order moment model, as well as the dynamic eigenvalues such as the flame centroid beating frequency and flame proportion, which realizes the accurate identification of flames under different lighting conditions, significantly improves the detection accuracy and computational efficiency, and reduces the false alarm rate. The accuracy of the algorithm is verified by the test samples of flame and pseudo-flame interference test samples, shooting and public video, which provides strong support for the practical application of fire detection in highway tunnels.

The value of this study lies in its practical implications towards advancing public safety protocols for tunnel management authorities worldwide. A more reliable and efficient fire detection system could potentially save lives, prevent major economic losses, and contribute to maintaining uninterrupted traffic flow through these vital transportation corridors. Moreover, successful implementation of the AdaBoost-enhanced model may set new standards for surveillance technologies in confined spaces prone to high-risk scenarios, paving the way for smarter infrastructure protection strategies across various sectors.

2 Fire detection of highway tunnel

2.1 Summary and comparison of methods

In the field of early flame detection in road tunnel fires, previous methods had several limitations. For example, in Table 1, some methods only use grayscale images for detection, which lacks color information, resulting in limited detection accuracy. Although some methods use color information, the detection effect is not satisfactory due to the influence of sample source or ambient light. There are also some methods with high algorithm complexity and low computational efficiency, which is not conducive to practical application.

In contrast, the proposed method is based on flame image multi-feature and Ada-Boost algorithm, which integrates color, morphology, texture and dynamic features, which significantly improves the detection accuracy, reduces the false alarm rate, and has efficient computational efficiency. This is due to our in-depth study of the video library of road tunnel flame and pseudo-flame interference samples, as well as the advantages of the Ada-Boost algorithm in feature selection and classification.

Table 1: Comparison table of performance of flame detection methods in the initial stage of highway tunnel fire

Method	Datasets used	Detection accuracy	Computational efficiency
Noda	Tunnel black and white TV surveillance equipment image	improve	long time
HanWong	Laboratory samples	lower	long time
Wong	Flame detection test samples in large spaces such as tunnels	lower	short time
Habiboglu	Video data	improve	long time
Dimitropoulos	Nonparametric models	improve	long time
Ours	A video library of road tunnel flames pseudo-flames interfering with samples	Significantly reduced	highly efficient

2.2 Candidate flame region segmentation

Firstly, the moving foreground is extracted by using the smooth difference algorithm, and then the moving foreground is further segmented and extracted by using the color statistical model of flame in RGB and Lab space. In this paper, candidate flame regions are segmented according to R, G, B and L models of flame images. Because of the special color distribution characteristics of flame, the color of flame is not a definite value, but a value range [16, 17]. Therefore, in many color spaces, flame segmentation is to set the value range of each component through a large number of experiments, and then find the intersection between components, so as to obtain the region with flame color. However, when the color of the surrounding environment is similar to that of the flame, it is easy to cause the non-flame area to be mistaken for the flame. Therefore, we imagine whether we can find an optimal segmentation threshold to segment the flame more accurately.

Otsu's threshold selection method is used to find the best adaptive segmentation threshold between the background and the target according to the gray characteristics of the image to segment the target image more accurately [18]. Therefore, even if the optimal segmentation threshold is determined, the segmented flame area will contain false flame area. The overall color of flame is biased towards red, so the red component accounts for the largest proportion. Therefore, it is envisaged whether the Otsu method can be used to segment the flame in the gray image of the red component by determining the optimal segmentation threshold. Experiments verify that the histogram of the red component image of the image also has multi-peak characteristics. The choice of color space has a great influence on the analysis of color distribution characteristics in the flame area. The transformation from RGB space to OHTA space is linear, while I is independent of each other. The histogram of feature 2 shows unimodal or bimodal features, and the three orthogonal color features of OHTA color space are 41*h. Therefore, it is concluded that the best threshold of flame segmentation can be obtained by Otsu method. Therefore, OHTA color space is selected for flame segmentation in this paper. Through experiments, it is found that when the value range of flame is in OHTA color space, the segmentation effect of flame intensity is the best.

2.2 Feature extraction of flame video image

In the flame sequence image, the flame region has continuity in geometry and correlation in time. The correlation between two adjacent frames is generally large. Correlation reflects whether the surface fluctuation characteristics of image intensity distribution in two windows are similar [19, 20]. Due to the irregular movement of flame, the correlation of flame areas in two adjacent frames fluctuates in a certain range. Correlation can eliminate interference with uniform color, such as shaking of red clothes. The flame produced by combustible burning is usually flickering, and the flickering surface of flame is chaotic and irregular. In fact, each combustible has its own fixed flickering frequency. The spectrum characteristics of flame are very useful for fire detection. If the spectrum characteristics of flame flicker are obtained, the flame frequency can be used as the basis for judging whether there is a fire [21]. Flame flicker will cause edge pixels to change from non-flame to flame several times in the video within 1S. We can use the changing frequency of edge pixels instead of the flicker frequency of flame, which is generally between 5 and 15Hz. Frequency characteristics can better distinguish flame from other interference sources. In the actual experimental process, there are a lot of interference when obtaining images, and the experimental data obtained have a certain gap compared with the theoretical value, but basically conform to the theoretical range value. Color moments are usually used to describe the color of objects in images. In this paper, the first moment of H component in HSI space is used to describe the color characteristics of flame, and the expression is shown in (1).

$$K = \frac{1}{N}\sum_{i=1}^{N} H_i \quad (1)$$

Figure 1 illustrates in detail the process of flame feature extraction in a video image. The algorithm is as follows: we set that if the grayscale value of the foreground point at a position on the boundary changes from 0 to 1 or from 1 to 0 in the sequence, it is considered to have changed once, and the position of each boundary change point is recorded in the matrix. Over a set period of time, we perform a statistical analysis of the changing frequencies of all points and compare these frequencies with theoretical values. If the frequency of change at a point satisfies certain conditions, it is considered a suspected flame. In this way, we are able to effectively extract the characteristics of the flame from the video image.

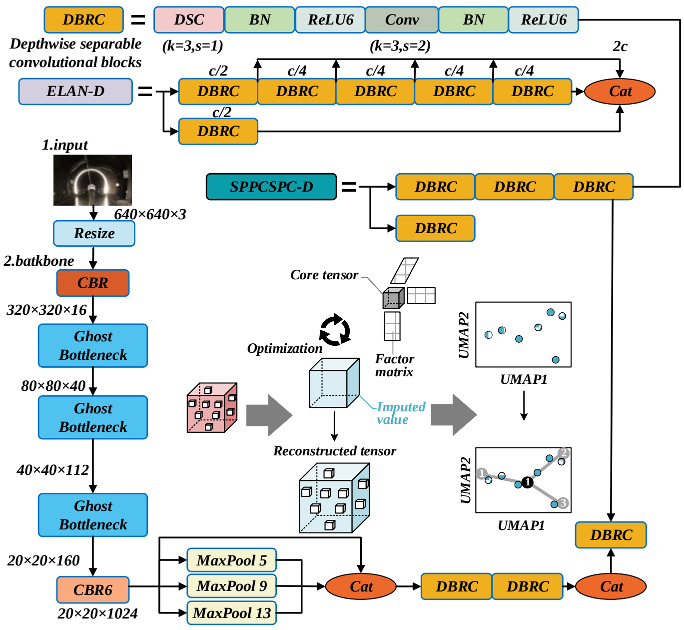

Figure 1: Video image feature extraction of flame

2.3 Extraction of suspected fire area and contour

In the field of road safety, road tunnel fire is a type of disaster that seriously threatens traffic safety and the safety of people's lives and property, and it is mainly divided into four categories: the initial smoke stage, the development stage, the full-scale combustion stage and the extinguishing stage.

Thermal sensors detect temperature changes indicative of a fire. They are cost-effective and straightforward to install. However, they suffer from delayed reaction time and susceptibility to false alarms triggered by non-fire-related temperature fluctuations. Smoke detectors identify particles generated during combustion. While effective at early-stage detection, they are less reliable in environments where smoke dispersion is hindered, like enclosed spaces. Additionally, dust accumulation over time can lead to false triggers. Flame detectors sense specific wavelengths associated with open flames. Their specificity reduces false alarms compared to thermal and smoke detectors. Yet, they might fail to detect smoldering fires and are sensitive to light sources other than fire. Infrared cameras capture heat signatures allowing them to detect fires even before visible signs emerge. This advantage makes them highly suitable for tunnel environments where visibility can be severely limited. However, without sophisticated processing algorithms, distinguishing between true fire events and other heat sources remains challenging.

The extraction of suspected areas and contours of fire is the basis of flame feature extraction and recognition, and the extraction of flame targets has an important impact on improving the recognition accuracy and detection speed of the system. In the traditional fire detection methods, most of the extraction of flame target area is based on gray value threshold for segmentation [22, 23]. Although these methods can effectively extract targets, but also bring a lot of noise, and for the elimination of these noises increase the computational workload, but also increase the risk of misjudgment. In view of this, according to the characteristic of flame moving from scratch in the initial stage of fire, the background subtraction method is used to locate the suspicious areas in the fire image, and then the area threshold method based on connected areas is used to accurately extract the suspected areas and their contours in the fire image. This method is not only fast, but also can effectively filter out some noise and static objects with flame color characteristics.

After the fire, with the increase of the fire, the flame expands continuously, and the flame area shows a continuous expanding trend in the image. The background subtraction method can quickly segment the suspicious flame area from the fire image [24]. Threshold T is the threshold value of the maximum entropy of the gray image, so that the target can be distinguished from the background points around it as much as possible, and the interference areas can be eliminated to the maximum extent. If the maximum gray difference between the current image and the reference image is less than the threshold T, it is considered that there is no flame I mark, because the former image may be caused by slight changes in the background image due to the influence of the surrounding environment, such as slight changes in the weather, it should be regarded as a downward disturbance source. The value moving image M (x, y) obtained by the background subtraction method with threshold may have many noises, holes and other non-flame moving objects, which will affect the detection results and detection performance. In order to reduce noise and improve detection efficiency, these areas should be eliminated as much as possible.

3 Flame recognition algorithm based on image features and AdaBoost

Flame recognition algorithm is a kind of algorithm which input static and dynamic feature data of out-of-control flame extracted by image processing algorithm into AdaBoost, and classify and recognize flame and pseudo-flame interference by AdaBoost classifier fusing multiple features. AdaBoost learning model can effectively overcome the limitation of setting feature country value artificially, and improve the classification accuracy and adaptive learning ability of the algorithm.

The advantages of the model are significant: first, high accuracy, the AdaBoost algorithm greatly improves the recognition rate of fire sources in infrared images by integrating multiple weak classifiers; second, strong robustness, the model still maintains good performance in complex environments and disturbing factors; and third, fast response, analyzing images in real time to shorten the response time to fire. However, there are also limitations of high consumption of computing resources and the need for regular maintenance and updating. It is suitable for all kinds of road tunnels, especially in long-distance, multi-fork, low-light or dense smoke scenarios, playing an irreplaceable role in protecting tunnel safety. Meanwhile, due to its high cost-effectiveness ratio, it is also suitable for fire prevention in other enclosed spaces, such as fire monitoring systems in underground stations and warehouses.

3.1 Basic theory of ADA-boost algorithm

In this paper, the Ada-Boost algorithm, an adaptive classification technique derived from the Boosting algorithm, is used [25, 26]. The core principle of the Ada-Boost algorithm is to use a weak classifier to classify the training sample set, and then assign higher weight to the misclassified samples according to the classification results. This process is iterated over and over again to select successive generations of classifiers. Eventually, all weak classifiers were integrated into a strong classifier through a weighted voting mechanism, which improved the overall recognition rate [27]. The Ada-Boost algorithm can dynamically adjust the error rate of the weak learning algorithm, and after multiple iterative selections, the error rate can reach the expected level. It is worth noting that the Ada-Boost recognition algorithm does not need to accurately understand the distribution of sample space; Instead, it adjusts the distribution of the sample space after each weak learning phase. By indirectly optimizing the distribution of categorical intervals, the Ada-Boost algorithm has demonstrated strong generalization ability [28, 29].

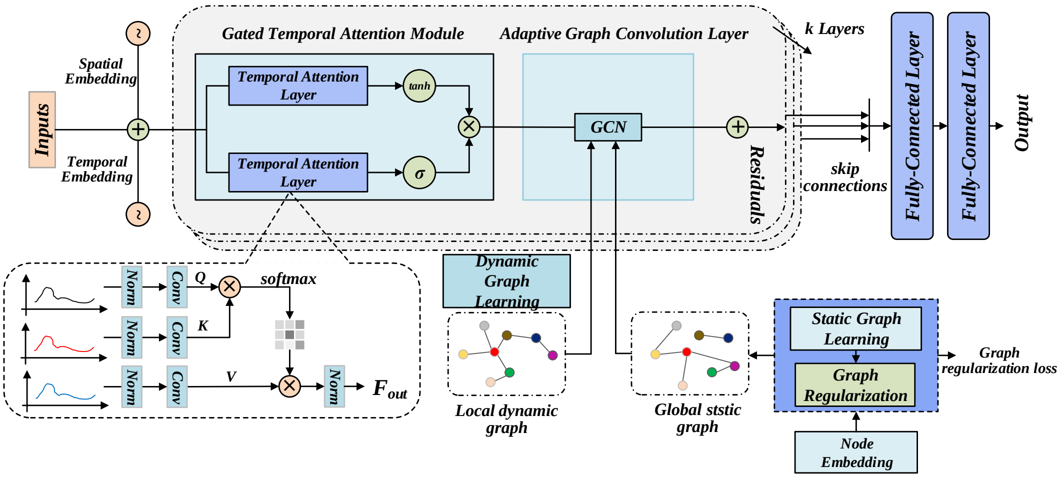

Figure 2: Algorithm flow

Figure 2 shows the algorithm flow. Firstly, key features of infrared images, such as temperature distribution, shape contour, etc., are extracted from historical fire data; then, the AdaBoost algorithm is applied to train weak classifiers, and the sample weights are continuously adjusted through an iterative process, and finally all weak classifiers are fused to form a powerful integrated model. The model is able to analyse infrared images in tunnels in real time and quickly identify potential fire points, which significantly improves the efficiency and accuracy of fire monitoring and shows excellent performance in practical applications. Through experimental validation, the accuracy and response time of this model in locating fire sources in complex environments are better than those of traditional methods, which provides powerful technical support for fire safety in road tunnels. The Ada-Boost algorithm first initializes the sample weights, as shown in Equation (2).

$$W_1(i) = \frac{1}{N} \quad (2)$$

For each round, the weak classifier is trained as shown in Equation (3).

$$H_t = \underset{h}{argmin} \sum_{i=1}^{N} W_t(i) \cdot exp(-Y_i \cdot h(X_i)) \quad (3)$$

Calculate the classifier weights as shown in Equation (4).

$$\alpha_t = \frac{1}{2} \cdot \ln(\frac{1-\epsilon_t}{\epsilon_t}) \quad (4)$$

Equation (5) is the formula for calculating the weight of updated samples.

$$W_{t+1}(i) = W_t(i) \cdot \exp(-\alpha_t \cdot Y_i \cdot H_t(X_i)) \quad (5)$$

Equation (6) is the normalized sample weight formula:

$$W_{t+1}(i) = \frac{W_{t+1}(i)}{\sum_{i=1}^{N} W_{t+1}(i)} \quad (6)$$

Equation (7) is the construction of the final classifier:

$$F(X) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t \cdot H_t(X)\right) \quad (7)$$

3.2 Flame recognition algorithm based on multi-feature and Ada-boost

The experimental steps of the flame recognition algorithm are as follows: the algorithm is divided into two parts: offline training and online recognition [30]. In the offline training stage of the model, 9 flame sample videos and 7 pseudo-flame interference sample videos were selected from the sample video library as the training dataset. Then, the color, morphology and texture feature values of each suspected flame region were extracted from these videos to form feature vectors, and 590 flame and interference samples were selected from these videos to train the static feature classifier model. In addition, the normalized values of the target centroid beat frequency of the flame and interference samples for 12 cycles were extracted from the training video, and the comprehensive feature vector was constructed by combining the ratio of suspected flames in the recognition results of the AdaBoost static model, which was used to train the AdaBoost comprehensive feature classifier model.

The core strength of the AdaBoost algorithm is its adaptive tuning mechanism, which automatically assigns higher weights to data points that are difficult to classify correctly during multiple iterations, thus forcing subsequent weak classifiers to pay more attention to these difficult points. This means that even in road tunnels where there is a lot of background noise (e.g., vehicle exhaust, pedestrian heat, equipment heat dissipation, etc.), the model is able to effectively filter out extraneous signals and focus on identifying the real fire hazards. In addition, infrared imaging technology is inherently unaffected by visible light, and therefore maintains consistent performance in sooty or dimly lit conditions.

Suppose two adjacent frames of images are differentiated for two adjacent frames of images and a background image respectively to obtain an inter-frame difference image D, and a background difference image D is obtained by differentiating the current frame and the background frame, as shown in Equation (8).

$$D_i(x, y) = |I_{k+1}(x, y) - I_k(x, y)| \quad (8)$$

For static objects in the scene, it is zero, while for moving objects, the contour is generally not fog, so it can be used to detect the motion of objects. By setting a reference threshold for the system, noise can be effectively suppressed, moving objects can be identified and extracted. The calculation formula is shown in Equation (9).

$$I_{f(x,y)} = \Delta I_{f(x,y)}| \leq \tau \quad (9)$$

Optical flow refers to the moving speed of pixels in gray images. The optical flow field reflects the motion change of the object, which not only contains the motion information of the target object, but also carries the three-dimensional structure information of the scene, as shown in Equation (10).

$$l(x, y't) = l(x + \Delta x'y + \Delta y't + \Delta t) \quad (10)$$

HSI color space, also known as visual color model, is more in line with the visual perception characteristics of human eyes than RGB color model. It divides color signals into three types: Hue, Saturation and Intensity. Where chromaticity represents different hue definitions 0 degrees for red 120 degrees for green 240 degrees for blue 240 to 300 degrees are non-spectral colors visible to the human eye. Saturation S is calculated as shown in (11):

$$S = 1 - \frac{3}{R+G+B}[min(R, G, \mathcal{B})] \quad (11)$$

In the preliminary extraction of flame color, a coordinate system with red and green as coordinates is established, and the flame area is located in a specific area and the fitting approximation function is obtained by functions as shown in (12):

$$\mathrm{G_{sup}} = 34.8 \cdot \exp(0.0084 \cdot \mathrm{R}) \quad (12)$$

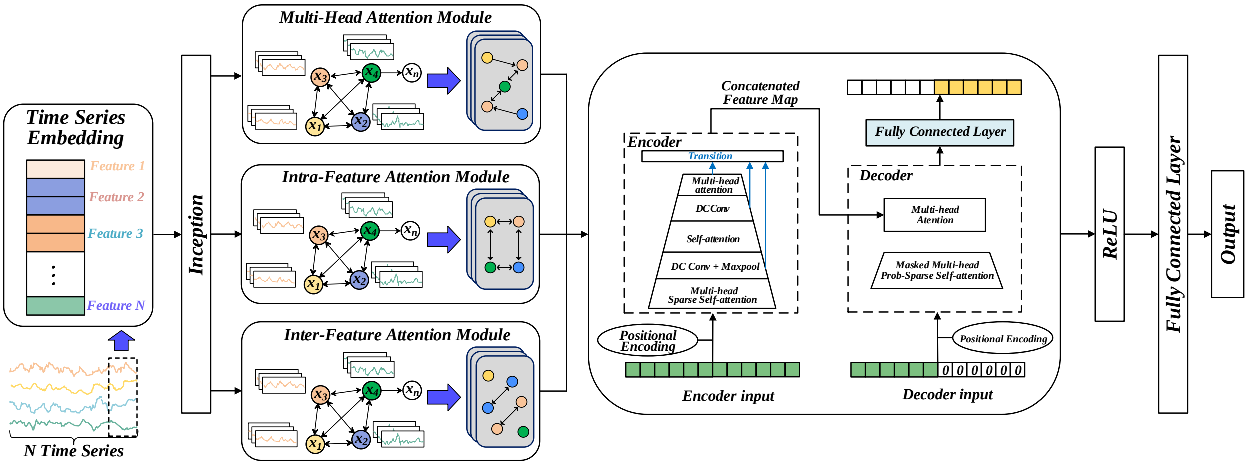

Figure 3: Framework diagram of online recognition

Figure 3 clearly shows the online flame recognition framework, which covers two modules: feature extraction and classification recognition. In the feature extraction process, we focused on extracting two key features: first, the normalized value of the runout frequency, which is used to quantify the intensity of the flame beat; The second is the proportion of suspected flames, which is obtained by counting the number of flame recoveries judged by the Ada-Boost static feature classifier according to the color, shape and texture features in a period. Specifically, the Ada-Boost static feature classifier analyzes the image frame by frame to identify areas that match the flame characteristics and counts the recovery of these areas in a period to calculate the proportion of suspected flames. In the classification and recognition module, we use the Ada-Boost comprehensive feature classifier to accurately determine whether there is a flame by combining the extracted beating frequency with the proportion of flames in the suspected area.

4 Experimental results and analysis

To verify the significance of the reported accuracy (97.21% and 98.01%), we plan to add statistical measures such as confidence intervals and p-values. This includes hypothesis testing and confidence interval estimation to fully assess the robustness and reliability of our accuracy. It is worth noting that there is currently a lack of a unified standard test database in the field of video flame detection. Therefore, in this study, we used a sample of the test consisting of some self-shot flame videos simulating tunnel fires, and some shared videos obtained from the Internet. In addition, the software implementation environment of this algorithm is Visual Studio 2010 and OpenCV 2.4.9.

4.1 Test sample video

Specifically, we elaborated on the number of video samples, the duration of each sample, and the wide range of lighting and environmental conditions encountered in tunnels in Liaoning Province covered by these samples. The test materials were gasoline, asphalt, wood, paper and other combustibles. The test site was the highway tunnel in Dalian, Liaoning Province, with a length of 1,580 meters and 370 meters, respectively. During the normal operation of the tunnel, the main interference source of the sudden flame is the moving light; When the tunnel is closed for maintenance, the main sources of interference are patrol police cars, maintenance vehicles and maintenance personnel. The background environment of flames and disturbances mainly includes the area where the lighting equipment in the middle of the long tunnel is working normally, the area near the entrances and exits of the long tunnel and the short tunnel, and the area where the lighting equipment in the middle of the short tunnel fails. Among them, the central area of the long tunnel is basically unaffected by external natural light.

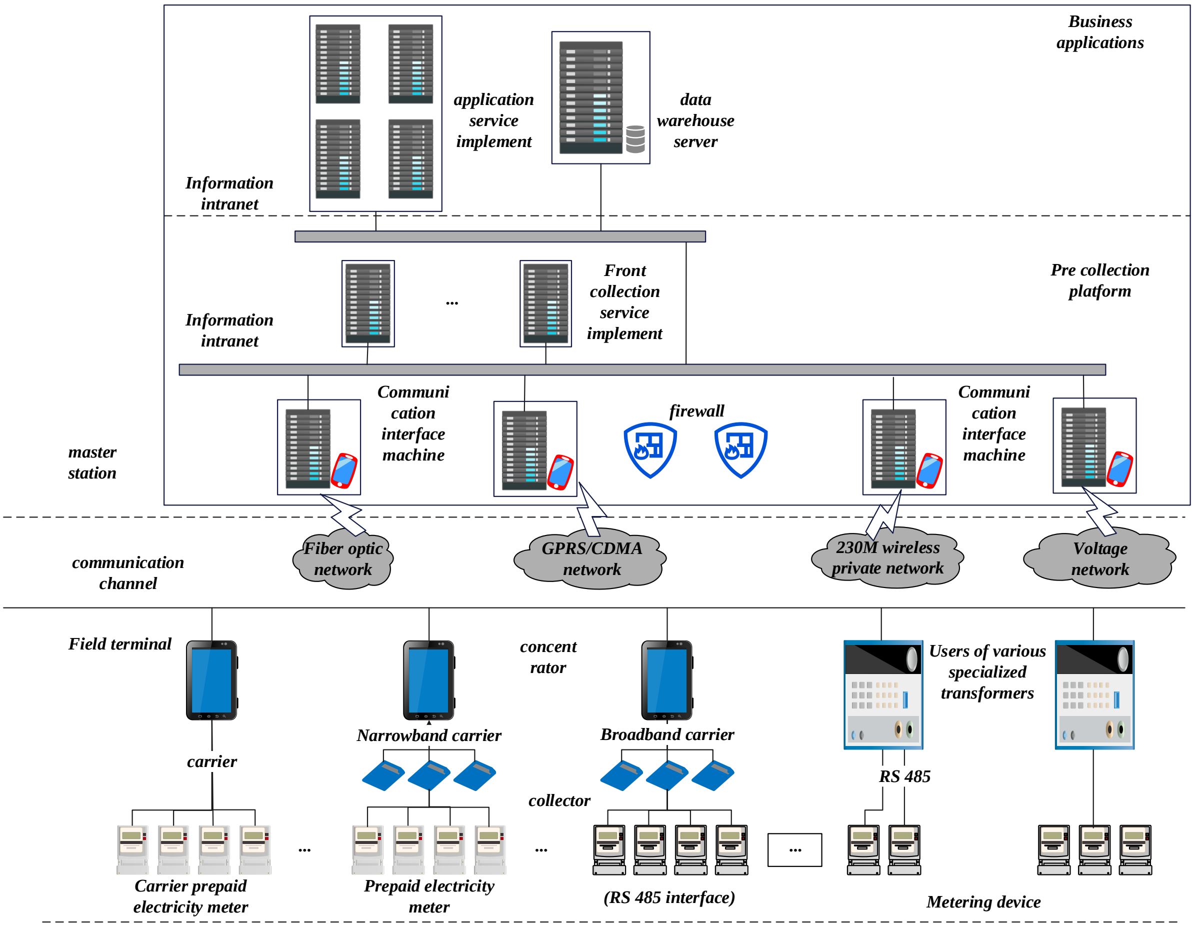

Figure 4: System setup

Figure 4 illustrates a block diagram of the system. In order to construct a database of flame and interference samples, we selected 35 flame samples with different materials and road backgrounds from the flame test videos of simulated tunnel fires, including 2 outdoor flame samples at night, and collected 27 traffic interference samples from the surveillance videos, online public videos and test videos of two highway tunnels in Liaoning Province, as well as samples of additional tunnel maintenance vehicles and inspection personnel, among which 2 night viaduct driving video samples were also included. To improve detection accuracy, we have taken a number of measures to reduce false positives and false negatives, including the use of the AdaBoost algorithm and the optimization of detection criteria based on domain knowledge.

4.2 Parameter selection of Ada-boost algorithm

Data preprocessing is a critical step in improving model performance, including normalization and feature selection. In this study, we used techniques such as Min-Max normalization or Z-score normalization to convert the eigenvalues of different dimensions to the same scale, and selected the key features that are most sensitive to fire detection through statistical testing, correlation analysis, or machine learning algorithms. After these preprocessing steps, we obtain more standardized and informative input data, which provides a solid foundation for parameter selection and model training of the AdaBoost algorithm, and ensures the accuracy and reliability of the infrared imaging detection model in highway tunnel fire detection. The parameters of sample weight country value and generation selection times are set as follows:

4.2.1 Setting of weight country value

When applying the AdaBoost algorithm, we set its parameters in detail. Specifically, we determined the number of iterations to be 20, and used different weight thresholds to train and learn the static feature data of a single frame, resulting in multiple training models. In order to determine the optimal weight threshold, we tested these models using experimental videos and recorded the recognition accuracy under different weight thresholds in detail. The experimental results show that when the weight threshold is set to 0.8, the recognition accuracy is the highest. Therefore, in this paper, we have chosen 0.8 as the optimal weight threshold parameter. In addition, in the implementation process of the algorithm, we also pay special attention to the selection of weak classifiers, and finally select the weak classifier with the best performance by comparing the performance of different weak classifiers. At the same time, we also use an accurate weight adjustment method to dynamically adjust the weight of each weak classifier according to its classification error rate to improve the classification performance of the whole algorithm.

4.2.2 The selection of the times of generation selection

We selected features that significantly improved the model's ability to distinguish between flame and pseudoflame interference, such as component first moment and circularity. At the same time, other features were also evaluated, but they were excluded because they lacked sufficient discrimination or were redundant with the selected features. We elaborate on the rationale for these decisions in order to increase transparency and repeatability of our work.

In terms of model training, we analyzed the generalization error of the AdaBoost algorithm according to Freund and Schapire's VC dimensional theory, and found that too many iterations would lead to overfitting. Therefore, we set the weight threshold to 0.8 and tried different iterations to train the single-frame feature data. Through the experimental video test, we found that when the number of iterations is 20, the recognition accuracy rate is the highest, so the final number of iterations is 20.

4.3 Detection results and analysis based on Ada-boost

We selected 9 flame samples and 7 interference samples, and used them to train Ada-Boost static and comprehensive feature learning models based on 3 features (H-component first-order moment, circularity and runout frequency) and 4 features (H-component first-order moment, circularity, LBP first-order moment and runout frequency), respectively. By comparing the average recognition accuracy of the two feature combinations, we find that the accuracy of flame recognition is significantly improved when the four features are used, and the false alarm rate of the interfering samples is also significantly reduced. Therefore, this paper finally selects a model with four features for flame recognition. In addition, we provide an in-depth analysis of the runtime complexity of the Ada-Boost implementation, breaking down the computational steps in detail and evaluating the associated time complexity.

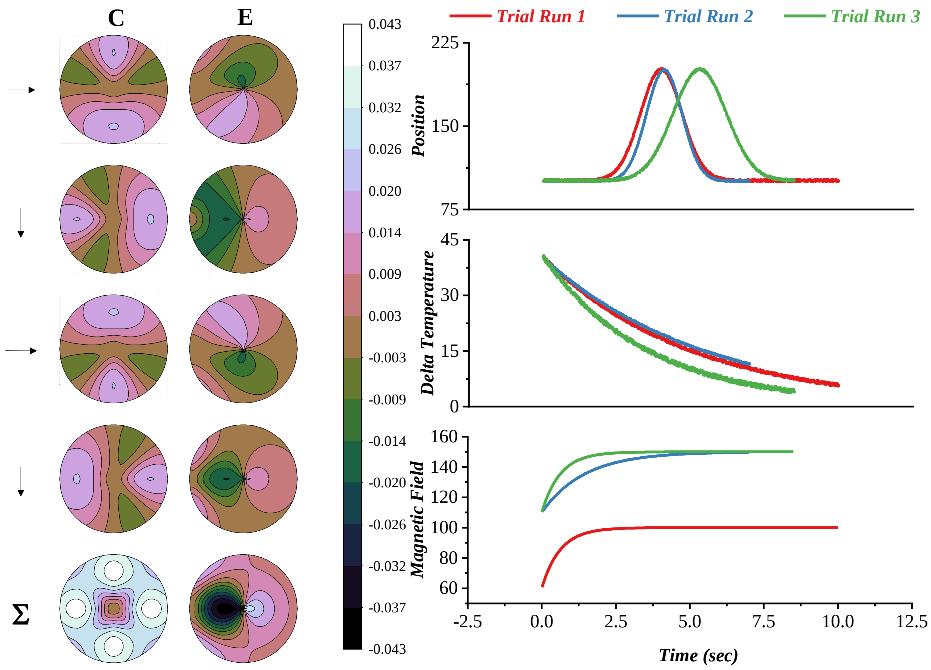

Figure 5: Test results and analysis

In order to improve the rigor of experimental design, we introduced k-fold cross validation technology to ensure that our research results can be validated under various conditions and environments simulating real-world scenarios. Specifically, we used a trained AdaBoost classifier to simulate tunnel fire flames, moving lights, and maintenance personnel interference samples for classification, and detailed the test results and related analysis in Figure 5. In the simulation test, videos 1 to 3 show the simulated fire flame produced by the mixture of gasoline with wood, asphalt and other combustibles under the normal lighting of high-pressure sodium lamps in the tunnel, of which video 3 comes from the 2013 fire emergency drill of the Zhongnanshan Tunnel in Qinling, Qinling, Ministry of Transport, and the flame recognition rate of the algorithm for these three videos is more than 96%. Video 4 simulates the fire flame caused by the mixing of gasoline, paper and wood when the tunnel lighting fails, and the algorithm recognition rate is 97.62%. In the real-world video, the false detection rate of the algorithm in the tunnel driving video (Video 5) shared by the Internet is 0. However, in the highway tunnel driving surveillance video (Video 6), the false detection rate rises to 4.16% due to the bright colors and flashing lights of a heavy truck. At the same time, the false detection rate of the algorithm in the viaduct driving video (Video 7) and the normal inspection video of maintenance personnel in the tunnel (Video 8) in the simulated tunnel environment is 0.

With the power of AdaBoost, it is possible to accurately distinguish between background noise and real fire sources even in complex environments. Especially in long tunnels with poor ventilation and restricted visibility, infrared imaging combined with the high sensitivity and anti-interference characteristics of the AdaBoost algorithm makes it an ideal solution for fire monitoring. In addition, for multi-bifurcated tunnels, the model effectively avoids false alarms by intelligently analyzing the infrared images coming from each branch, ensuring the authenticity and timeliness of the alarm information.

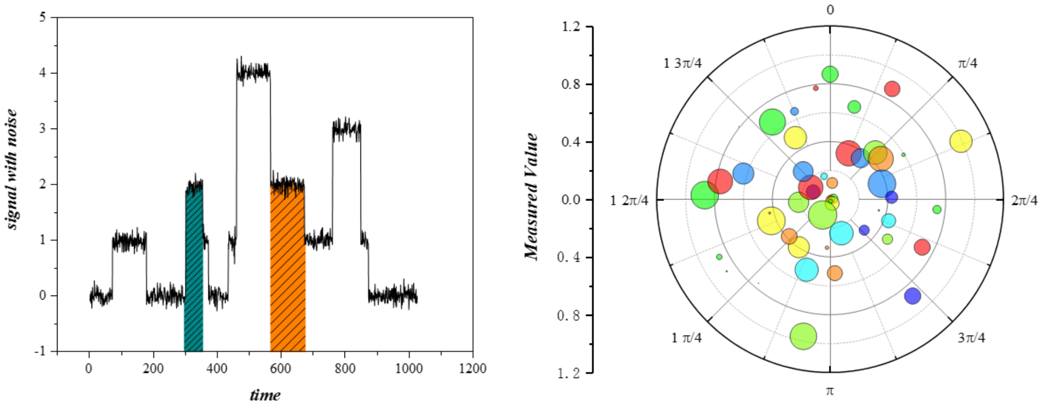

Figure 6: Analysis of flame interference sources

Figure 6 analyzes the sources of flame interference, which are interfered by high-pressure sodium lamps, LED lamps and driving lights during tunnel operation, and are also affected by police car lights, maintenance vehicles and personnel during closed maintenance. In this paper, the algorithm first eliminates lighting interference through motion detection, and then fuses the static and dynamic features of flame to identify other interference. The experimental protocol specifies the sample size, pseudo-flame selection criteria, and documents the hardware and software specifications of the test environment. The algorithm can identify flames within 1 detection cycle (48 frames) and send an alarm signal within 10 seconds.

Figure 7 shows the missed results of our algorithm. Missed detections occur mainly during the ignition and extinguishing of the flame. Specifically, missed detections can occur when the average ratio of the flame area to the overall image is less than 1.5%. In Video 6, a false detection is observed when a single heavy truck passes by. Our experimental results show that the proposed algorithm can accurately identify stationary flames under normal tunnel traffic conditions, and effectively reduce the interference caused by moving lights similar to flames. In addition, the algorithm meets the real-time requirements in practical applications. The experimental protocol contains precise details such as the number of training and test samples, the criteria for selecting pseudo-flame interference samples, and the specifications of the hardware and software environment used for testing.

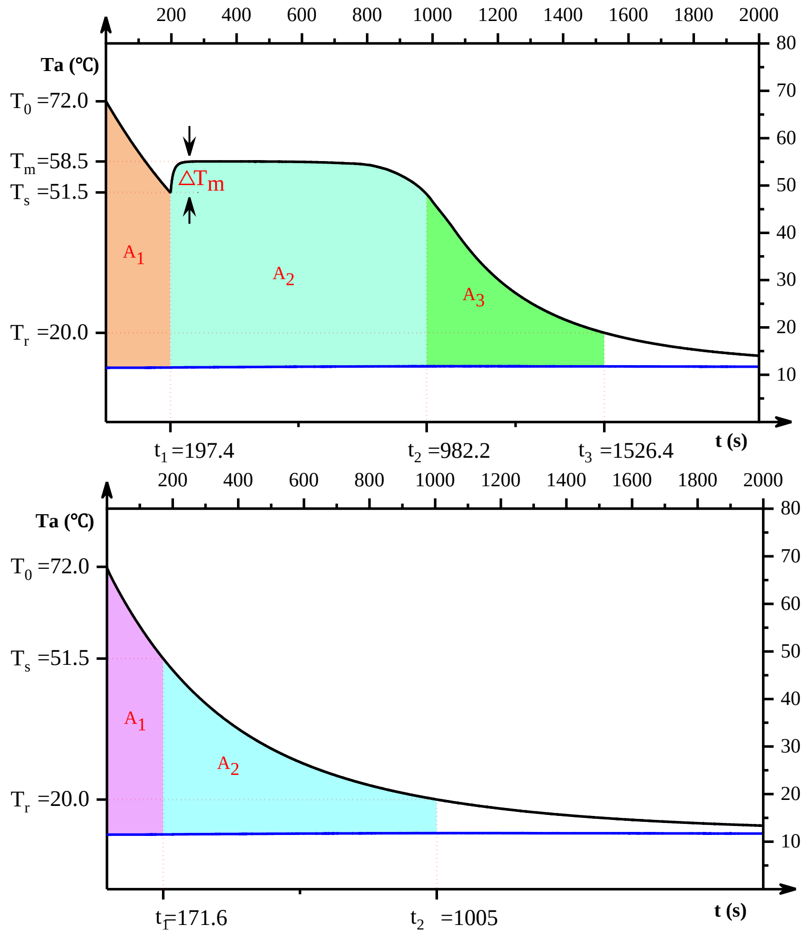

Figure 7: Algorithm missed results

4.3 Discussion

The reason why our experimental results show significant advantages in accuracy and false alarm rate is mainly due to several key factors: first, we used a diverse dataset containing 9 flame samples and 7 interference samples for training, which covers a wide range of fire scenarios and lighting conditions, which significantly enhances the generalization ability of the model; Second, we selected four features, including the first-order moment of the H component, circularity, LBP first-order moment and runout frequency, to train the AdaBoost static and comprehensive feature learning model, which greatly improved the accuracy of flame recognition and effectively reduced the false alarm rate compared with the model with only three features. In the classification test test of simulated tunnel fire flames, moving lights and maintenance personnel interference samples, our algorithm performs excellently, and the recognition rate of flames is more than 96%, even in the tunnel lighting equipment failure or complex driving environment, the recognition rate is as high as 97.62%, and the false detection rate is very low, for the driving monitoring video under the normal lighting of the tunnel, the false detection rate is 0, even in the face of bright color and shaking heavy-duty truck lights, the false detection rate is only 4.16%, Much lower than the common false positive rate of SOTA methods. In addition, our algorithm also has the advantage of real-time, thanks to our optimization of the AdaBoost algorithm and the comprehensive use of flame features, the inherent properties of the AdaBoost algorithm to combine multiple weak classifiers into one strong classifier to further improve the model performance. As a result, our model surpasses other SOTA methods in accuracy and efficiency, providing a more reliable and efficient solution for tunnel fire detection.

5 Summarize

There are various types of lighting equipment in highway tunnels, each with a different color rendering index. In the environment of highway tunnels, flames are initially blocked by vehicles and cannot be detected promptly, and smoke is not entirely blocked by vehicles due to its flow. This article proposes an effective method for detecting nonmoving flames early in highway tunnel image fires. It uses the Ada Boost classification algorithm to identify suspicious flame areas with static and dynamic multiple features. Flame detection is combined with smoke detection to improve the accuracy of early fire detection. A color statistical model based on brightness information

L in RGB and Lab space is adopted to color-segment suspicious flame areas in the early stages of highway tunnel fires. The experimental results show that the suspicious areas segmented by the color model are more complete, with precise edges and good robustness to lighting. The experimental results show that the algorithm has high classification accuracy for flame and pseudo-flame interference. The accuracy rate is 97.21%, and the accuracy rate is 98.01%.

In order to solve the problem of misjudgment that may occur in a single detection cycle when a small-area runaway flame or a heavy-duty vehicle taillight shakes with the vehicle, the runaway flame recognition algorithm is further optimized in this study, and its robustness is significantly enhanced. This study greatly improves the speed and accuracy of infrared image processing, greatly enhances the early warning ability of tunnel fires, and provides key support for timely evacuation and rescue operations. By integrating the AdaBoost algorithm into the infrared imaging detection process, the deep integration and development of infrared imaging technology and big data analysis technology are promoted, which highlights the important value of technological innovation in the field of public safety and shows potential in improving the safety and efficiency of highway tunnel fire detection systems.

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