Fire Detection Method Based on Improved Fruit Fly Optimization-Based SVM

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Abstract: Aiming at the defects of the traditional fire detection methods, which are caused by false positives and false negatives in large space buildings, a fire identification detection method based on video images is proposed. The algorithm first uses the hybrid Gaussian background modeling method and the RGB color model to perform fire prejudgment on the video image, which can eliminate most non-fire interferences. Secondly, the traditional regional growth algorithm is improved and the fire image segmentation effect is effectively improved. Then, based on the segmented image, the dynamic and static features of the fire flame are further analyzed and extracted in the area of the suspected fire flame. Finally, the dynamic features of the extracted fire flame images were fused and classified by improved fruit fly optimization support vector machine, and the recognition results were obtained. The video-based fire detection method proposed in this paper greatly improves the accuracy of fire detection and is suitable for fire detection and identification in large space scenarios.

Keywords: Fire detection, image segmentation feature extraction, fruit fly optimization, support vector machine.

1 Introduction

In recent years, the frequency of fires has increased, such as large-scale construction fires, mine fires, forest fires, and tunnel fires. Attributing to human beings is a huge loss, but it also destroys the ecological environment on which human life depends, and even directly threatens human life. Countries around the world have invested enormous human, material and financial resources in fire prevention and firefighting. While improving

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traditional fire protection equipment, many researchers have begun to study how to detect fires as soon as possible and eliminate the fire in the bud.

Traditional fire detectors generally use temperature or smoke sensors. When a fire occurs, fire parameters such as combustion gases, smoke, temperature, flame, and burning sound are often accompanied by fire parameters [Chiu, Lu, Chao et al. (2014)]. Measurements and analysis of these fire parameters can be used to determine the measured values. There is no fire in the area. Sensitive components are used to effectively respond to such information as smoke, gas, temperature, and flame, and the device for measuring fire parameters is called a fire detector. The fire detector is a sensor device that converts these physical quantities representing fire information into electrical signals. In 1847, the American dentist Charm and the Myanmar University professor Farmer developed the world's first sending device for urban fire alarms, 1890 In the United Kingdom, the first heat-sensing fire detector was successfully developed. Since then, humans have created a new era of automatic fire detection and alarm technology. Since then, with the development of science and technology, fire detection technology has also developed rapidly.

This type of detector is widely used in fire alarms in small spaces such as buildings and tunnels. However, in high-altitude fire alarms, the above methods are not very suitable. Only when the fire occurs to a certain extent, the sensor fire detector can sense the fire and then alarm; it is difficult to meet the requirements of early detection of such fires. At this time, if the environmental conditions are harsh and there are a lot of disturbances, such as dust, light, vibration, etc., it may easily lead to increased detection noise or even sensor failure.

In view of the above-mentioned problems in fire detection, taking into account that the flame and smoke appear in the visible light field with certain color, texture and shape image characteristics, in recent years, people began to consider the use of computer vision features to improve the efficiency of fire detection. With the continuous development of digital image processing technology, multimedia, microprocessor and pattern recognition technology, a fire detection technology based on video image processing came into being.

People use the camera as a detector to collect the continuous image information of the monitored object in real time, detect the fire information directly from the sequence diagram through the intelligent identification technology, and perform linkage processing such as alarm and save [Borges and Izquierdo (2010)]. Compared to traditional methods, this video-based detection method can detect fires in the shortest time, and accurately indicate the origin of the fire and the size of the fire, so that it is easy to control the spread of fire and reduce the damage caused by the fire. And reduce casualties. At present, it has attracted widespread attention from scholars at home and abroad.

The video-based fire detection method proposed in this paper is mainly based on the following methods: Firstly, it uses the hybrid Gaussian background modeling method and the RGB color model to perform fire prejudgment on the video image [Truong and Kim (2012)]. If video is suspected to contain fire in advance, the improved method is adopted. The region growing algorithm performs image segmentation, extracts the suspected fire flame area, then further analyzes and extracts the dynamic and static features of the fire flame in the suspected fire flame area, and finally uses support vector machine with fruit fly optimization to extract the dynamics of the fire flame image. Feature fusion and classification would result in recognition results.

2 Related work

After these years of development, people currently judge the existence of flames in digital images mainly from two aspects. One is to judge through the static characteristics of the flame, such as the color brightness of the flame, to determine the threshold value of the flame brightness component in the HSI space of the image. The second is to judge through the dynamic characteristics of the flame. Such as flame area changes, flame frequency characteristics.

Han et al. [Han and Lee (2006)] used image processing techniques to detect flames and smoke in real-time using tunnel environments. The existing tunnel environment fire detection algorithm is difficult to apply due to different environments. The author proposes a special tunnel fire algorithm. The author proposes the original algorithm for the tunnel environment. The specific location of early events can be detected by obtaining information from color and motion to reduce false detections in the tunnel. However, in real-time applications, this method is not applicable due to the large number of heuristic thresholds.

Lin et al. [Lin, Liu, Zhao et al. (2014)] analyzes the development status of forest fire monitoring and fire detection and early warning at home and abroad, adopts digital video surveillance, digital image processing and pattern recognition methods to analyze and identify forest fire occurrence images, and increases forest fires in forest fires. The fire detection and warning system with smoke video detection intensity, dynamic analysis of flame characteristics, etc., alarms at the early stage of the fire to reduce the fire damage.

Nguyen-Ti et al. [Nguyen-Ti, Nguyen-Phuc and Do-Hong (2014)] proposed an early-stage fire detection method based on regional growth. This method uses the color and motion information extracted from the video sequence to detect the fire. It can work indoors and outdoors. In addition, it detected a fire at the beginning of the combustion process and provided an earlier response than a conventional fire detector. The method identifies the color pixels in the scene by the region growth segmentation, and then identifies the moving pixels according to the ratio of the height and the width of the suspected fire zone and the correlation coefficient. This method can achieve a lower false alarm rate by eliminating the same color as fire because it only requires one firing pixel as the seed pixel.

Jia et al. [Jia, Lin, Wang et al. (2016)] proposed an adaptive flame segmentation and recognition algorithm to improve the adaptability and detection rate of spacious building video fire detection systems. First, the foreground is moved in the video and the brightness of the moving area is calculated to estimate lighting conditions. Different flame color segmentation models are selected adaptively for different lighting conditions. After a series of segmentation and post-processing, the suspicious flame area was extracted for feature analysis. Then, using a trained support vector machine to distinguish the flame area from the non-flame area.

Wang et al. [Wang, Li, Yao et al. (2016)] proposed a flame detection method combined with color cues to achieve a new method of flame detection based on analytic hierarchy process (AHP) multi-feature fusion.

Han et al. [Han, Jin, Wang et al. (2017)] makes full use of the fire characteristics and color information. First, background subtraction motion detection based on Gaussian mixture model is used to extract moving objects from the video stream. Then, in combination with RGB, multi-color based detection of HSI and YUV color space was used to obtain possible fire zones to achieve the purpose of fire detection.

Wang et al. [Wang, Wu, Zhang et al. (2016)] proposed a fire smoke detection algorithm based on optical flow and texture features that can be used for early fire alarms. It establishes the image of the pyramid and uses LBP and LBPV to extract static texture features at different levels. Due to the turbulent characteristics of the smoke motion, the direction of the smoke is consistent, and the optical flow vector analysis method is used to determine the direction of movement of the suspicious area contour and reduce the computational complexity. Finally, the SVM identifies the texture features of the smoke image.

Gomes et al. [Gomes, Santana and Barata (2014)] introduced a fire detection method based on a vision-based stationary surveillance smart camera. This method integrates several well-known technologies that properly address the challenges associated with the actual deployment of vision systems. Specifically, background subtraction is performed using a context-based learning mechanism to achieve higher accuracy and robustness. The computational costs of frequency analysis of potential fire areas are reduced by focusing on their attention mechanisms. In order to quickly distinguish between fire areas and fire moving objects, a new color-based fire appearance model and a new wavelet-based fire frequency feature model are proposed.

3 Image segmentation based on improved region growing

3.1 Traditional regional growth segmentation algorithm

Region growing is a relatively old image segmentation algorithm. This method is usually implemented in two ways. One is to first give a small part or seed region within the target object to be extracted in the segmented image, and then use the seed region as the standard and continue to add pixels near it to some areas with certain specified criteria for growth, eventually achieve growth as a target to be segmented; the second is to first divide the image into many more consistent, such as within the region. A small area with a similar pixel gray value will be increased to a large area according to the specified criteria, and the target object will be segmented and extracted. The common shortcoming of the regional growth method is over-segmentation, which is, dividing the image into many regions. In order to solve this problem, Ma et al. [Ma, Son and Hazle (2016)] proposed an improved region growing algorithm. The improved methods are: 1) automated quality guidance for determining the sequence of region growth, and 2) consideration when selecting output vectors two candidate vectors, 3) Automatic segmentation during region growth to handle spatially isolated objects. Popov [Popov (2017)] proposed a region growing algorithm for interferometric phase unwrapping of radar images.

Region growing is a kind of image segmentation algorithm with serial area segmentation. Its advantage is that the algorithm is relatively simple. It can basically segment regions with the same characteristics and can provide better image boundary information and segmentation effect. When no a priori information is available, the best performance can be achieved, and it can be used to segment relatively complex images such as natural scenes.

3.2 Image segmentation based on improved region growing color space selection

Flame detection based on color space is a very convenient, fast and common flame area extraction method. However, as people's living and workplace construction structures become more and more complex, higher requirements are imposed on the efficiency of fire detection. The requirement for the segmentation of the flame area should be accurate, rapid, and other high-quality effects. Although RGB is the most basic color component of an image, the RGB color model is greatly affected by the light intensity. Once the light is enhanced, the effect of segmentation will be reduced. This model is suitable for indoor and other scenes that are not exposed to light. The YCrCb color model is less affected by light, and it is the closest to the human visual perception. Its brightness and chromaticity are more easily to separate. In this paper, the regional growth combined with YCrCb method is used to segment the fire flame image.

The literature [Alewijnse, Buchin, Buchin et al. (2018)] concluded through a large number of experiments that the flame constraint formula in the YCbCr color space is:

$$\begin{cases} Y(x,y) > Cb(x,y) \\ Cr(x,y) > Cb(x,y) \\ Y(x,y) > Y_{mean} \\ Cb(x,y) > Cb_{mean} \\ Cr(x,y) > Cr_{mean} \\ \left|Cb(x,y) - Cr(x,y)\right| \geq \tau \end{cases} \tag{1}$$

Through the above-mentioned YCbCr color model's distribution law of flame, it can be used as similarity area growth pixel similarity criterion.

3.3 Flame seeds screening and region growing

The content of this article is based on real-time video. The pixels in the image satisfying the mixture Gaussian model can be extracted by the method in Chapter 3, and the suspected flame pixels are selected according to the judgment conditions of the YCbCr color model. Thus, the screened suspected flame pixels are treated as growing seeds, and then the area is grown until the complete flame is segmented.

O(*x,y*) is denoted as the image after the mixed Gaussian model, and F(*x,y*) is the original image. First compare O(*x,y*) with the original image F(*x,y*), and use the YCbCr color model as a criterion for the pixels with the same position, and select the suspected fire pixels. The selected pixel is regarded as the seed point for the growth of the subsequent region, i.e., the flame seed. After judgment selection, use C(*x,y*) to represent fire seeds.

The entire region grows as follows:

(1) Vi(*x,y*) is used to mark whether the pixels in the image are traversed. If the pixel Pi(*x,y*) has been traversed, Vi(*x,y*) has a value of 1 and 0 otherwise.

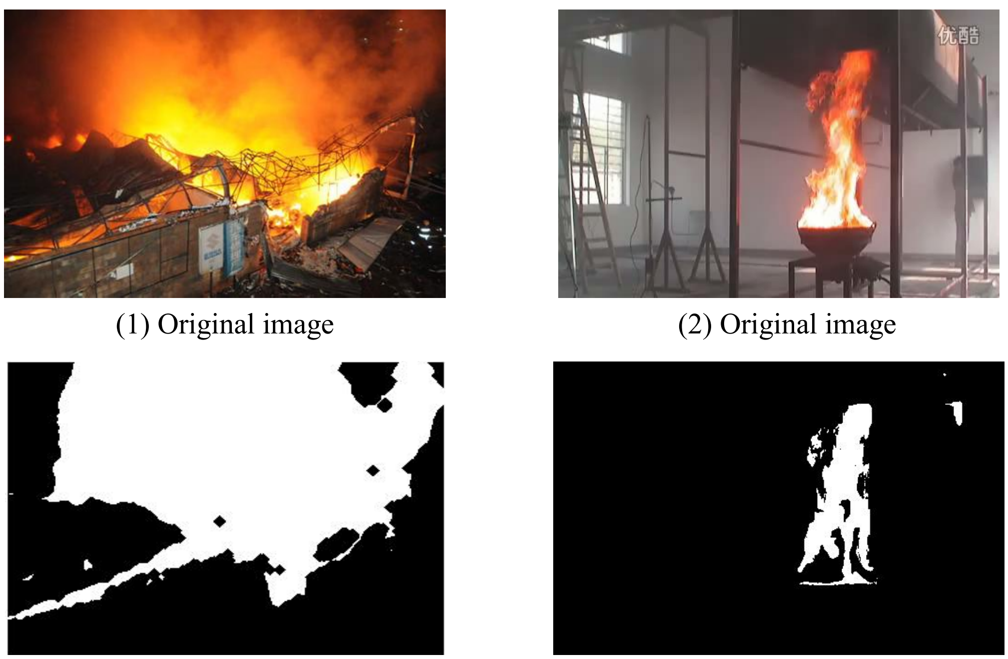
(2) The point Pi(*x,y*) which maps the flame seed mark Mi(*x, y*) to the original image F(*x, y*) is the starting point of the region growth, and the mark Vi(*x,y*) is 1 at the same time.

Traverse the eight neighborhood points around the point Pi(x,y) and use the YCbCr model to determine whether it is a fire pixel. If one of the traversed pixels is a fire pixel, mark its M(x,y). The value is 1, and at the same time, the V(x,y) value is marked as 1; otherwise, the M(x,y) value is unchanged and the V(x,y) value is 1.

(3) If an ergodic point Pi+1(x,y) is determined to be a fire pixel, it can be used as a new flame seed, and step (2) is repeated. Until the pixel value of the eight points around a certain pixel is 1, the return to the previous starting point continues eight-neighborhood traversal until returning to the most original point P(x,y).

3.4 Segmentation effect based on improved region growth

In this paper, the flame image segmentation based on improved region growth is proposed. The mixture of Gaussian model and YCrCb color model is used to select the growing seeds, which has good real-time performance. The fire flame image segmentation method proposed in this paper (segmentation effect is shown in Fig. 1) can extract the flame area better and greatly improve the accuracy of flame detection.



(1) Original image (2) Original image

(3) Segmentation image (4) Segmentation image

Figure 1: Fire image segmentation based on this paper's method

3.5 Research and extraction of fire image features

3.5.1 Area change

In the early stage of a fire flame, the flame area continuously increases during the combustion process. For this feature, the flame growth rate and the average flame area can be used to determine the characteristics of the increasing flame area.

It is assumed that the areas of the N images continuously collected at a constant time t areS1, S2, S3…, SN. Calculate the rate of change of the area of two adjacent images:

$$\Delta d_i = \frac{S_{i+1} - S_i}{\mathrm{t}} \tag{2}$$

The average of the top *N* image areas:

$$S_m = \frac{1}{N}\sum_{i=1}^{N} S_{\mathrm{i}} \tag{3}$$

The image feature parameters are extracted through the above two. For different environments, the values of Δd_i and S_m vary. However, for a fire or a fixed light source with a relatively stable combustion state, the value of Δd_i is close to 0, and S_m is basically a constant value. This feature removes unnecessary interference and improves the efficiency and reliability of fire detection. However, if a fixed light source, such as a lamp, moves toward the camera, this method will generate a false alarm, so this method must be combined with other features to perform fire detection.

3.5.2 Circularity

The degree of circularity C is mainly used to describe the complexity of the shape of an object. The general source of interference for fire is a relatively smooth and regular shape of a street lamp, a lamp, etc. The shape of the image of the flame is more complicated. This feature can be a good source of interference which can be used as one of the criteria for detecting the flame. Its general formula is:

$$C = P^2/A \tag{4}$$

where *P* denotes the perimeter of the flame boundary and *A* denotes the flame area. It is the minimum value of circularity, and the shape complexity is proportional to the C value. For the sake of observation, this paper normalizes the inverse of (4) by 4π and multiplies it by 4π to a number between 0 and 1. The formula is as follows:

$$\mathrm{C} = \frac{4\pi A}{P^2} \tag{5}$$

3.5.3 Texture features

Texture is a visual feature that reflects the homogeneity of an image embodies the intrinsic properties common to the surface of the object, contains important information about the structure of the surface structure of the object, and their association with the surrounding environment [Zhou, Wang, Zhang et al. (2016)]. The spatial distribution of the flame color values differs from the objects with similar flame color values, i.e., they have different textures. In this paper, the gray image co-occurrence matrix is used to analyze the texture features of the flame image. Using this method, texture features such as energy, correlation, entropy, and contrast can be obtained. Assuming that the gray level is L, the energy, correlation, entropy, and contrast are described as follows.

(1) energy

The energy is expressed by using the sum of the squares of the values of the gray-level co-occurrence matrix, which reflects the uniformity of the image gray distribution and the texture thickness. If the distribution of the gray-level co-occurrence matrix is more uniform, then the energy value is relatively small; If the distribution of gray-level co-occurrence matrix is more scattered, and the value of some places is relatively small, then the energy value will be relatively large. Energy formula is as follows:

$$f_1 = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p_{ij}{}^2 \tag{6}$$

Among them, (i,j) is the gray value of any point in the image; P_{ij} is the probability that the gray value (i,j) appears.

(2) entropy

Entropy is a measure of the amount of image information, which reflects the degree of inhomogeneity or complexity in the image texture. If the distribution of gray level co-occurrence matrix is more uniform, then the value of entropy is relatively small; conversely, if the distribution of gray level co-occurrence matrix is relatively dispersed, then the value of entropy will be relatively large. The formula is as follows:

$$f_2 = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} P_{ij} \log_2 P_{ij} \tag{7}$$

4 Fire detection method based on improved fruit fly optimization-based SVM

4.1 Support vector machine algorithm

SVM is a supervised learning model based on statistical learning principles and is mainly used for the processing of classification and regression analysis data [Cho and Hoang (2018)]. SVM can also be used in computer security monitoring to prevent information leakage. The SVM [Chen, Lu, Yeung et al. (2018)] seeks to find the optimal separation plane, as shown in Fig. 2, which contains two different kinds of data, the first type (circles) and the second type (squares) of dataset classifications, and SVM finds the best in both classes. The hyperplane (linear boundary) maximizes the distance between the two parallel boundaries (the distance between the boundary of each class and the nearest point). The nearest recent data is support vector.

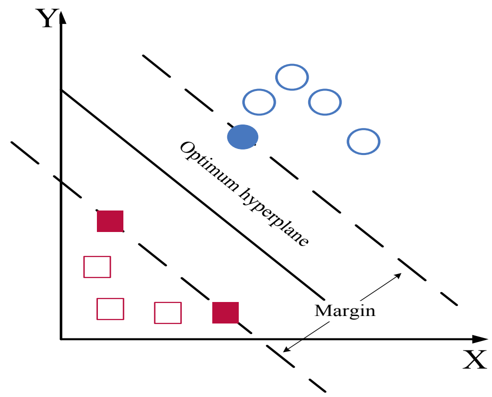


Figure 1: The example of SVM data classification

The goal of SVM is to seek the best compromise solution based on limited sample information between model complexity and learning ability, and to obtain the best generalization ability with expectation.

The basic principle of SVM is as follows: If the given data set is $G=(x_i, y_i)$, where $i=1,\ldots,n$, $x\in R^d$, $y\in \{-1,+1\}$ is the category number when When $y_i=\pm1$, it indicates the category to which x_i belongs.

The general expression of the linear discriminant function is:

$$g(x)=\omega'\cdot x+b \tag{8}$$

The classification gap is $2/\|\omega'\|^2$. When $\|\omega'\|^2$ takes the minimum value, it meets the requirement of maximum classification gap. The standard SVM model is:

$$\begin{cases} \min \varpi(\omega') = (\frac{1}{2}\|\omega'\|^2 + c\sum_{i=1}^{1}\varepsilon_i^{\,2}) \\ s.t. \quad y_i(\omega'^T x_i + b) \geq 1-\varepsilon_i \\ \varepsilon_i \geq 0, \quad i=1,2,\ldots,n \end{cases} \tag{9}$$

where ω′ is the inertia weight; c is the penalty parameter; ε is the slack variable; b is the constant SVM transforms linearly inseparable sample data by non-linear transformation Φ: $R^d\rightarrow H$ to transform the original low-dimensional spatial sample data into high-dimensional space H, and uses the linear method to create the best classification surface. In the solution, a functional theory is used to construct a $K(x_i, x_j)$ suitable for Mercer's requirements. The formula can be expressed as:

$$Q(\alpha) = \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j K(x_i, x_j) \tag{10}$$

where α_i is a Lagrange multiplier. The best classification discriminant function is:

$$f(x) = \mathrm{sgn}\left\{\sum_{i=1}^{n}\alpha^* y_i K(x_i \bullet x + b^*)\right\} \tag{11}$$

Among them, the function K(xi , xj) is a kernel function. In this paper, the kernel function of the SVM adopts Radial Basis Function (RBF), which can be expressed as:

$$K(x,y)=\exp(-\sigma\|x-y\|^2) \tag{12}$$

where σ is the RBF nuclear parameter, substituting the above formula into formula (12), the best classification discriminant function is:

$$f(x)=\operatorname{sgn}\left\{\sum_{i=1}\alpha_i^* y_i \exp(-\sigma\|x-y\|^2)+b^*\right. \tag{13}$$

The algorithm complexity and classification effectiveness of the SVM model mainly depend on the value of the penalty factor c and the nuclear parameter σ. If c is too large, the classification accuracy of the training sample data set may be too high, but it will affect the generalization performance of algorithms. If the value of c is too low, the classification of the test sample data set may not reach the expected accuracy. If σ is too large, over-learning may occur and the generalization ability of the algorithm becomes lower. If σ is too small, under-study problems may occur, resulting in a decrease in classification performance. Therefore, the fruit fly optimization algorithm is used to optimize the parameters c and σ of the SVM.

4.2 Fly fruit optimization algorithm (FOA)

The FOA is a global optimization algorithm based on the fruit fly search process proposed by the Taiwan scholar Pan WT in 2011 [Pan (2012)]. This algorithm has the advantages of fewer parameters, higher search precision, and simple algorithm, and is widely used in algorithm optimization. Engineering practice [Zhang, Wu, Guo et al (2016); Yu, Li, Li et al. (2016)].

The iteration process of FOA is shown in Fig. 3:

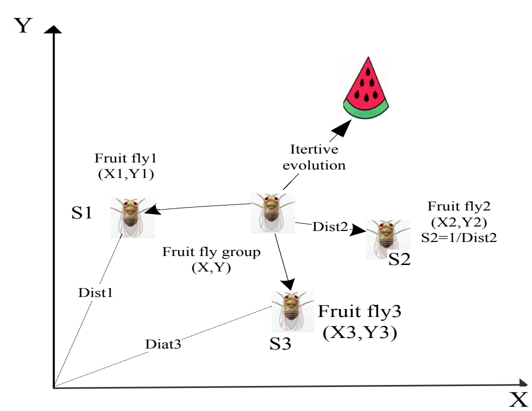


Figure 3: The iteration process of FOA

The steps are as follows:

(1) Fly fruit population initialization. Fly fruit population total: N; total number of iterations: Gmax; random assignment of population position: X_axis, Y_axis.

(2) Randomly give directions and distances for FOA. RandomValue is the search distance:

$$X_i = X_{\_axis} + RandomValue\,() \tag{14}$$

$$Y_i = Y_{\_axis} + RandomValue\,() \tag{15}$$

(3) First, calculate the Disti and Si of each fruit fly, where Disti is the length of the individual and the origin of the fruit fly, and Si is the reciprocal of the Disti, indicating the fruit flesh taste concentration determination value:

$$Dist_i = \sqrt{X_i^2 + Y_i^2} \tag{16}$$

$$S_i = \frac{1}{Dist_i} \tag{17}$$

(4) In the expression of taste concentration (i.e., fitness function), input Si to obtain the taste concentration of fruit flies individual Smelli:

$$Smell_i = \text{Function}(S_i) \tag{18}$$

(5) Find the fruit flies that have the best concentration of flavor in the fruit fly population (suitable for maximization issues):

$$[\text{bestSmell} \;\; \text{bestindex}] = \max(Smell_i) \tag{19}$$

(6) Record and save the best taste concentration bestSmell with its X, Y coordinates, and the fruit fly group flies to this location:

$$\text{Smellbest} = \text{bestSmell} \tag{20}$$

$$X_{\_axis} = X(\text{bestindex}) \tag{21}$$

$$Y_{\_axis} = Y(\text{bestindex}) \tag{22}$$

(7) Finally iteratively optimizes and repeats Steps (2) to (5). When the taste concentration is no longer better than the previous taste concentration or when the number of repetitions reaches the maximum number of iterations, the cycle stops.

4.3 Improved fly fruit optimization

The main influencing factors of the performance of the fruit fly optimization algorithm are: initial fruit fly position, fruit fly population size, and iterative search step size. The initial position of the fruit fly is determined by the independent variables of the function. Although increasing the size of the population will make the optimization of fly fruit more accurate, the algorithm will take longer and the convergence speed of the algorithm will not increase. The traditional FOA in the iterative optimization in the search step is fixed, if the search step is too large, the FOA's global optimization ability is strong, but in the optimization search process is likely to miss the best solution; If the search step is too small, then it has a stronger local search ability, which can obtain a local optimal solution, but the search process is likely to fall into a local optimal solution, and cannot find the global optimal solution. Therefore, how to choose the right iterative search step is the key to improving the optimization performance of fly fruit.

This paper proposes an Improved Step-by-Step Clustered Fruit fly Optimization Algorithm (Improved FOA, IMFOA). In the original Fruit fly optimization algorithm flow, the Fruit fly population is divided into two groups: good-group and poor-group. To calculate the individual fruit flavor concentration, bestSmell is the current best flavor concentration in fruit flies, Smelli is the flavor concentration of the current flies i, and a is a parameter that determines the degree of similarity, which is a random number of (0, 1). Fruit fly colony determination formula is as follows:

$$a_i = \frac{Smell_i}{bestSmell} \geq \alpha \tag{23}$$

The Fruit fly individuals that satisfy the above formula are assigned to the good-group, and the remaining individuals are assigned to the poor-group.

The iteration step Lg of the good-group is:

$$L_g = \frac{(L_{\max} + L_{\min}) - \dfrac{(L_{\max} - L_{\min})(G-1)}{G_{\max} - 1}}{2} \tag{24}$$

where Lmax is the maximum iteration step size, Lmin is the minimum iteration step size, Gmax is the maximum iteration number, and G is the current iteration number.

The iteration step Lb of the difference poor-group is:

$$L_b = \frac{(L_{\max} + L_{\min}) + \dfrac{(L_{\max} - L_{\min})(G-1)}{G_{\max} - 1}}{2} \tag{25}$$

At the beginning of the algorithm, the moving step length is $(L_{max}+L_{min})/2$. After the first iteration is completed, the population is divided into two categories according to the clustering judgment formula. Then, the two groups search according to their respective iteration steps. After the search is completed, all the fruit flies are regrouped according to the group's judgment formula and searched according to their respective iteration steps until the number of iterations reaches the maximum value.

After each sub-item is divided into poor-group, the good-group and the poor-group are searched according to their respective iteration steps. It can be seen from the above formula that the search step length of the good-group changes from large to small as the number of iterations increases, and the improved local optimization ability of the fruit fly optimization algorithm is enhanced to avoid missing the local optimal solution. On the contrary, the difference poor-group search step length changes from small to large as the number of iterations increases, and the global optimization ability of the algorithm is enhanced, which avoiding the algorithm falling into a local optimal solution during the optimization process. After each iteration, the fruit fly population was rearranged and the two groups were then optimized with each iteration step. The improved fruit fly optimization algorithm can make up for the premature convergence of the original fruit fly optimization algorithm into the local optimal value, and also avoid the situation that the local optimal value is missed because the search step is too large.

5 Improved performance verification of improved fruit fly optimization algorithm

To verify the performance of the improved fruit fly optimization algorithm, six test functions were used to test the POS, TSPOS [Zhang, Li, Zhang et al. (2011)], FOA, and IMFOA four optimization algorithms. Tab. 1 shows the specific formula of the test function. Tab. 2 shows the mean and standard deviation of the test function obtained by the four algorithm optimization. It can be seen from Tab. 2 that IMFOA is significantly better than the other three algorithms according to the accuracy of the average and standard deviation of the six test functions. Fig. 4 is an iterative graph of the test function under four algorithm optimizations (in order to facilitate the display of the curve, the objective function of the test letter is taken as a logarithm of 10), and the IMFOA and The FOA's search capability is obviously better than the POS and TSPOS algorithms. Compared with the FOA algorithm, the convergence speed and the optimized accuracy of the IMFOA algorithm are better.

Table 1: Test functions

Function	Functional	Ranges
f_1	$f_1(x)=\sum_{i=1}^{n} x_i^2$	[-100,100]
f_2	$f_2(x)=\sum_{\mathrm{i}=1}^{\mathrm{n}}[x_i^2+10\cos(2\pi x_i)+10]$	[-5.12,5.12]
f_3	$f_3(x)=\frac{1}{4000}\sum_{\mathrm{i}=1}^{n} x_i^2-\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})+1$	[-600,600]
f_4	$f_4(x)=\sum_{\mathrm{i}=1}^{\mathrm{n}}\lvert x_i\rvert+\prod_{\mathrm{i}=1}^{n}\lvert x_i\rvert$	[-10,10]
f_5	$f_5(x)=\sum_{\mathrm{i}=1}^{n} ix_i^4+rand()$	[-1.28,1.28]
f_6	$f_6(x)=\sum_{i=1}^{n}(\sum_{j=1}^{i} x_j)^2$	[-100,100]

Table 2: The results' Comparison of algorithm optimization

Function		POS	TSPOS	FOA	IMFOA
f_1	mean	20.5941	7.3	1.2783e-07	6.4621e-08
	std	94.2031	55.5	8.6087e-07	4.7862e-07
f_2	mean	193.33	246.12	3.6106	2.8595
	std	166.59	155.07	5.2123	5.7392
f_3	mean	0.400	0.71	3.5880e-09	2.2277e-09
	std	0.2261	0.124	1.7590e-08	1.4412e-08
f_4	mean	17.28	17.88	2.8256e-04	2.0950e-04
	std	43.12	42.99	5.3789e-04	4.2929e-04

f_5	mean	2.1537e+03	2.0618e+03	5.0843e-04	3.3884e-04
	std	1.3731e+04	1.3743e+04	6.6342e-04	0.0023
f_6	mean	899.74	381.0869	1.1337e-07	9.0958e-08
	std	4.8351e+03	2.8065e+03	7.1642e-07	7.4006e-07

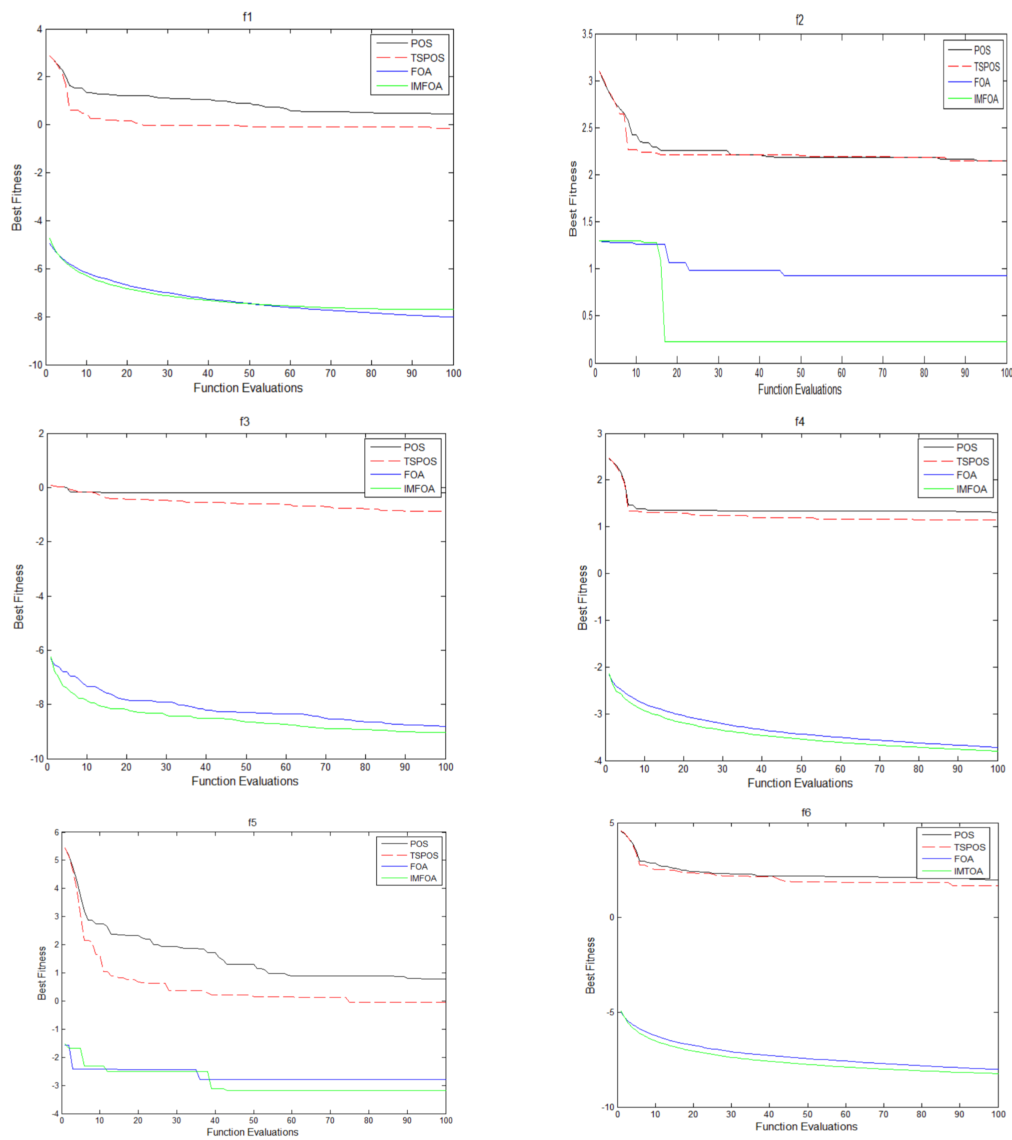


Figure 4: Adaptation function evolutionary curves of f_1-f_5 with four optimization algorithms

6 Experimental results and analysis

In order to verify the effect of the improved fruit fly optimization algorithm on the parameters of the optimized SVM, four different scenes of forest fire, indoor flame, open flame and mine flame were selected for the experiment. Fig. 5 and Tab. 3 show four scenarios. Video fire conditions, environmental conditions.

Video 1 Forest fire

Video 2 Indoor fire

Video 3 Empty fire Video

Video 4 Mine fire

Figure 2: Samples of videos

Table 3: Description of videos

Videos	Description of the videos
1	Description of the video
2	Indoor flame, large fire, bright red color
3	Empty flames, small fires, less affected by the surrounding environment
4	Coal mine underground flame, lack of light, dark environment, obvious flame characteristics

Four experiments were performed on four video flame images using POS-SVM, TSPOS-SVM, FOA-SVM, and IMFOA-SVM. Tab. 4 shows the experimental results.

Table 4: Results of fire detection

Video	The number of images	POS-SVM	TSPOS-SVM	FOA-SVM	IMFOA-SVM
1	150	91.0	91.7	91.7	93.1
2	150	93.1	94.5	95.2	96.6
3	150	84.8	85.5	86.2	88.9
4	150	95.2	95.9	95.9	97.2

Tab. 4 shows the verification experiments for the four fire detection and identification algorithms. Under the same environment and fire, POS algorithm has the lowest detection and recognition accuracy of fire images. The reason is that the genetic algorithm is due to the parameters. Many disadvantages, such as premature convergence and premature failure, cannot achieve optimal results in optimizing SVM and thus affect the accuracy of fire identification. The fire detection and recognition experiment using FOA-SVM algorithm, the accuracy rate is greater than or equal to the accuracy of POS-SVM and TSPOS-SVM, because parameters of FOA algorithm are less, the algorithm is simple and other advantages in the optimization of SVM parameters better than the POS algorithm. The IMFOA-SVM algorithm has the highest fire image recognition accuracy among the four algorithms. This is because the improved FOA algorithm avoids premature convergence and falls into the problem of local extremum, and improves the ability of the FOA algorithm to search for global optimal values. Experimental results show that the improved FOA algorithm can improve the accuracy of SVM parameter optimization. Thus, it can improve the accuracy of SVM model fire detection and recognition.

7 Conclusion

This paper mainly studies the video-based fire detection and identification. Firstly, we use the hybrid Gaussian background modeling method and the RGB color model to pre-judge the video image. If the pre-judged video is suspected to contain fire, then the improved region growing algorithm is used. Image segmentation, extraction of suspected fire flame areas, and then further analysis and extraction of dynamic and static characteristics of fire flames in suspected fire flame areas. Finally, the dynamic characteristics of the extracted fire flame images are merged and classified using fruit fly optimization support vector machines. The identification result. The video-based fire detection algorithm proposed in this paper filters out most of these interference and improves the accuracy of fire detection.

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