Research on Image Fire Detection Based on Support Vector Machine

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***Abstract*—In order to detect and alarm early fire timely and effectively, traditional temperature and smoke fire detectors are vulnerable to environmental factors such as the height of monitoring space, air velocity, dust. An image fire detection algorithm based on support vector machine is proposed by studying the features of fire in digital image. Firstly, the motion region is extracted by the inter-frame difference method and regarded as the Suspected fire area. Then, the uniform size is sampled again. Finally, the flame color moment feature and texture feature are extracted and input into the support vector machine for classification and recognition. Data sets were formed by collecting Internet resources and fire videos taken by oneself and the trained support vector machine was tested. The test results showed that the algorithm can detect early fire more accurately.**

***Keywords*—Fire detection, SVM, Machine learning**

I. INTRODUCTION

According to the preliminary statistics of the Fire Rescue Bureau of the Ministry of Emergency Management of the People's Republic of China [1], 237,000 fires were reported nationwide in 2018, resulting in 1407 deaths, 798 injuries and direct property losses amounting to 3.675 billion yuan. As one of the most common disasters in society, fire has the features of sudden occurrence, rapid spread and difficulty in fighting. It severely threatens the safety of human life and estate and affects the harmonious and stable development of society. Therefore, timely detection and alarm of fire is of great significance for fire fighting and safety evacuation.

Traditional fire detection technology mainly uses physical parameters such as air temperature and smoke concentration to judge whether there is a fire or not. Traditional flame detectors are vulnerable to environmental factors such as the height of monitoring space, dust, airflow speed and so on, which lead to false alarm and missed alarm.

With the rapid development of Computer Science in recent years, fire detection technology based on video image processing technology has also developed rapidly. Image fire detection technology uses camera to monitor and then input the video image to the computer to extract the fire image characteristics and then use the corresponding machine learning or depth learning algorithm to judge, so as to give an alarm. Image fire flame detection technology can overcome the shortcomings of traditional fire detection technology and has the advantages of quick response, accurate detection and rich information.

In the HIS color space model, Horng [2] et al. used the frame difference method to obtain the moving region as the suspected region of the flame. Chen [3] et al. combined RGB and HIS color criterion to extract Suspected fire region, and judged whether there was flame by judging the area growth and stability of the center of mass of suspected region. Phillips [4] et al. proposed a fire detection method based on color feature and motion feature. Jenifer [5] researched the feature vectors of skewness, area change, color and roughness of boundary contour of flame area, and then used Bayesian classifier in machine learning model for classification and recognition. Jilin [6] used color model to segment the flame area, and then extracted visual features such as dynamic, shape, texture and skewness in the suspected fire area. Finally, the Fisher linear discriminant method and Bayesian classifier in machine learning model are applied to detect fire. Han Xianfeng [7] et al. combined RGB, HSI, YUV three color models to segment the fire suspected areas, and then used the Gauss mixture model to detect the fire. All the above algorithms use color model to extract suspected fire areas, but there are some shortcomings when using color model to segment, such as background can not be completely filtered out and there are holes in the flame regions, which will affect the extraction of fire features, and is not conducive to subsequent fire detection.

In this paper, an image fire detection algorithm based on Support Vector Machine (SVM) is proposed based on the establishment of positive and negative fire samples data sets. In order to overcome the shortcomings of holes in the flame area, the algorithm uses scene classification method in remote sensing field to bring some background to the flame area then extracts the RGB feature, texture feature and color moment of the flame to get the feature vectors, and finally inputs the support vector machine model which trained before for fire judgment. The simulation results show that the algorithm can overcome the weaknesses of color model segmentation and improve the accuracy of detection.

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II. DETERMINATION OF SUSPECTED FIRE AREA

A. Segmentation Based on Color Model

In order to decrease the complexity of operations and improve the detection efficiency, flame regions are usually segmented before extracting flame features. Literature [8] through some simulation experiments, it is found that in the RGB color space model, the R, G and B components of the flame region satisfy (1).

$$R \geq G \geq B \tag{1}$$

Therefore, a fire suspected region segmentation algorithm based on RGB color space model is proposed which extracts R, G and B components of each pixel in the image, keeping the original pixel values of the pixels satisfying the above-mentioned relationship; setting the pixel values of the pixels that do not satisfy the above-mentioned relationship to 0,and the segmentation effect of the algorithm is shown in Fig.1.

(a) (b)

Fig. 1. Segmentation effect image. (a) original image. (b)Segmentation image.

Based on the above shortcomings, many scholars have been studying in order to improve the segmentation algorithm. In reference [9], a king of improved segmentation algorithm was put forward which combined R, G, B components of RGB color space model with S components of HSV color space model to segment flame image. The segmentation conditions need to satisfy (2).

$$\begin{aligned} &R \geq G \geq B \\ &S > \frac{(255-R)\times S_T}{R_T} \end{aligned} \tag{2}$$

The segmentation effect of the algorithm proposed in reference [9] is shown in Fig.2. From the segmentation results, we can see that the improved segmentation algorithm is better than the RGB color space model segmentation algorithm, which completely separates the foreground from the background, but there are still some voids in the flame area. Voids in the flame area will affect the extraction of flame features which is adverse to the later detection of fire.

(a) (b)

Fig. 2. Segmentation effect image. (a) original image. (b)Segmentation image.

B. Scene-based Classification

In view of the phenomenon that the flame region will be voids when the color model is used for segmentation. In this paper, the outer rectangle of the flame area is obtained and used as a Suspected fire area, as shown in the green rectangle box in Fig.3 (a). Then the flame area is brought with some background by using scene classification method in remote sensing field, as shown in Fig.3 (b). Finally, the uniform image size is sampled again. This overcomes the problem of using color model to segment Suspected fire areas.

(a) (b)

Fig. 3. Motion detection. (a) Motion Detection Map. (b)Motion area.

III. FIRE IMAGE FEATURES EXTRACTION

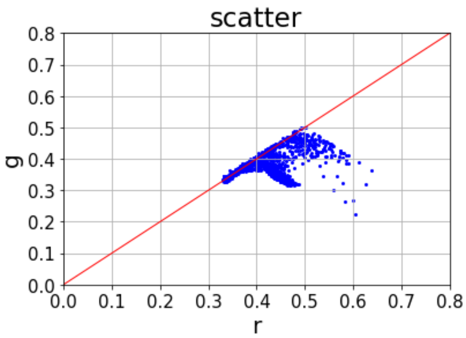
A. RGB Feature

In fire image, the color difference between flame and surrounding objects is obvious. Flame color is the most basic feature. Therefore, color information of fire plays a significant role in image fire recognition. Many different color space models have been proposed, such as RGB, HSI, HSV, YCbCr, YUV and L*a*b.

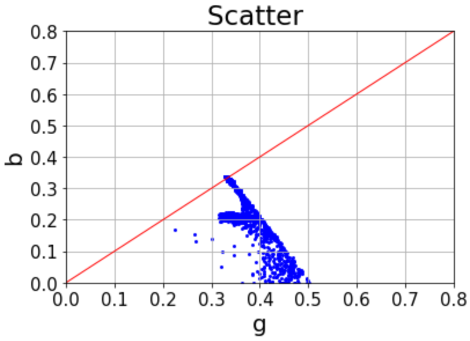
As shown in Fig.4, the R, G and B components of each pixel in the rectangular region are computed and normalized by (3) and then scatter plots are made, as shown in Fig.5.

$$r = \frac{R}{R+G+B}, g = \frac{G}{R+G+B}, b = \frac{B}{R+G+B} \tag{3}$$

Fig. 4. Fire Image.



(a)



(b)

Fig.5. Scatter plot. (a)r-g Scatter plot. (b)g-b Scatter plot.

From Fig.5, it can be seen that the value of R component is larger than that of G component and the value of G component is larger than that of B component.

B. *Color Moment*

Color moment is a kind of effective and simple method of color feature representation proposed by Stricker and Orengo [10]. The distribution of any color in an image can be described by color moment. Low-order color moments can accurately describe the color distribution information. Usually, first-order, second-order and third-order moment can be used to express the color distribution information in images and the mathematical formulas are shown in (4):

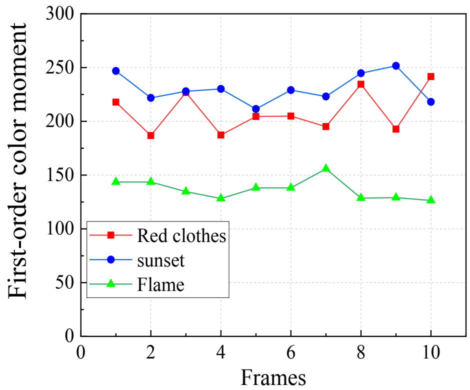
$$
\begin{aligned}
M_1 &= \frac{1}{N}\sum_{1}^{N} P_i \\
M_2 &= \left[\frac{1}{N}\sum_{i=1}^{N}(P_i - M_1)^2\right]^{\frac{1}{2}} \\
M_3 &= \left[\frac{1}{N}\sum_{i=1}^{N}(P_i - M_1)^3\right]^{\frac{1}{3}}
\end{aligned}
\tag{4}
$$

Where P_i represents the component value of the ith pixel in the fire suspected area, N is the total number of pixels in the fire suspected area, the first moment indicates the mean value, the second moment represents the standard variance, and the third moment represents the skewness.

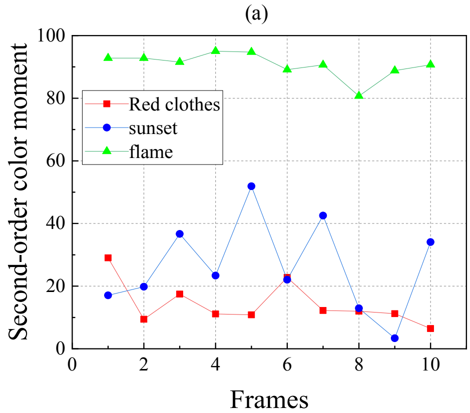
In this paper, 10 frames of fire images and common interferences (red clothes, sunset) images are collected respectively, As shown in Fig.6. the first, second and third order color moment of them are calculated respectively, and the broken line charts are given as shown in Fig.7.

(a) (b) (c)

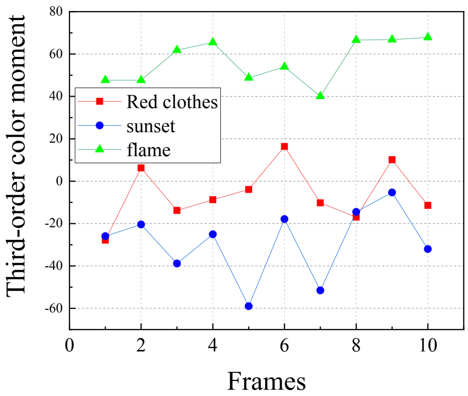
Fig.6. Scatter plot. (a)fire image. (b)Red clothes. (c)Sunset.



(a)



(b)



(c)

Fig.7. Line chart Of Color moment. (a)First order moment. (b)Second order moment. (c)Third-order moment.

From Fig.7, it can be seen that the lower order color moments (first, second and third order color moments) of fire images are obviously different from those of interferences, which can distinguish flame from interferences. Therefore, color moment can be used as a criterion for fire detection.

The RGB color space is transformed into HSV color space. The first moment of H component can also represent the color characteristics of flame. The formula is as follows((5)):

$$K = \frac{1}{N}\sum_{i=1}^{N} H_i \tag{5}$$

Where Hi represents the h-component value of the ith pixel in the fire suspected area, and N is the total number of pixels in the fire suspected area. The first moments of H component of 10 frames of fire images and common interferences are calculated and the broken line chart is drawn as shown in Fig. 8.

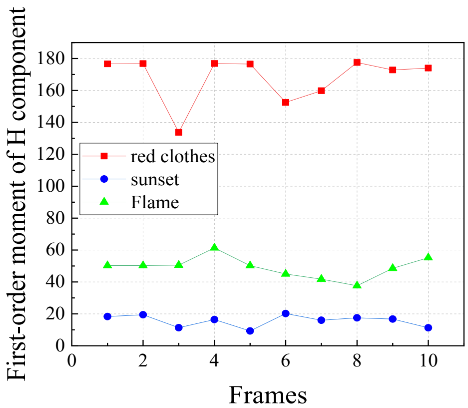


Fig.8. Line chart of First-order moment of H component.

As can be seen from Fig.8, the first moment of H component of flame mainly concentrates on about 170 which is quite different from that of interferences. The first moment of H component can be used to identify and detect fires.

C. *Texture Feature*

Texture is a common visual phenomenon and one of the important features in image analysis. Each object surface has its own texture features. There are many methods for describing texture features, In this paper, gray level co-occurrence matrix which a classical method for describing texture features is selected [11].

Take any point (x, y) in the image and take another point (x + a, y + b) in a certain step and direction to form a point pair. If the gray value of the point pair is (f1, f2) and the point (x, y) is moved on the whole image, different (f1, f2) values will be obtained. The number of occurrences of each (f1, f2) value is counted and then arranged into a square matrix. The total number of occurrences of (f1, f2) is used to normalize them into probability P (f1, f2). The resulting matrix is a gray level co-occurrence matrix. Generally speaking, the usual step sizes are - 1, 0, 1 and the angle is 0 degrees, 45 degrees, 90 degrees and 135 degrees.

Because of the large dimension of gray level co-occurrence matrix, it is not used as a feature to distinguish texture directly, but as a feature to classify texture based on some statistics constructed by gray level co-occurrence matrix. Haralick [12] has proposed 14 statistics based on gray level co-occurrence matrix, such as correlation, differential moment and inverse difference moment. Baraldi [13] et al. considered contrast and energy as the most effective features by studying six of them. Here are two statistics.

1) Angular Second Moment

The mathematical expression of angular second moment is as follows((6)):

$$ASM = \sum_{i}\sum_{j} p(i, j)^2 \tag{6}$$

Energy is the sum of squares of the elements of gray level co-occurrence matrix which is also called angular second moment. It is a measure of the uniformity of gray level change of image texture, reflecting the uniformity of gray level distribution and texture thickness.

2) Contrast

The mathematical expression of contrast is as follows((7)):

$$Con = \sum_{i}\sum_{j} (i-j)^2 p(i, j) \tag{7}$$

Contrast is the moment of inertia near the principal diagonal line of the gray level co-occurrence matrix. It reflects how the values of the matrix are distributed and reflects the clarity of the image and the depth of the texture grooves.

Still select the above collected 30 frames of fire images and common interference images, calculate two statistics, and make broken line charts as shown in Fig.9.

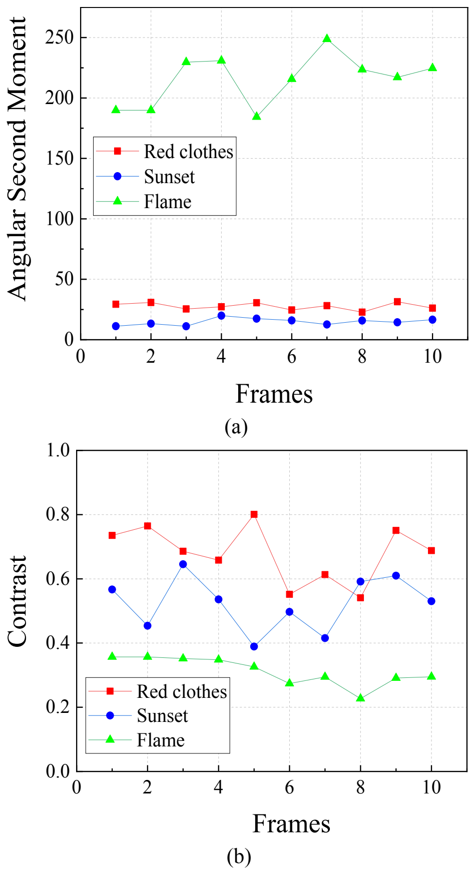


Fig.9. Texture features. (a)Angular second Moment. (b)contrast.

From Fig.9, we can see that the statistics (energy and correlation) constructed by gray level co-occurrence matrix can distinguish the flame from the disturbance, and can describe the texture features of the flame area. Therefore, texture features can be used as an effective criterion for flame image recognition.

IV. FIRE DETECTION ALGORITHM BASED ON SVM

A. Basic Principle of SVM

Support Vector Machine (SVM) was proposed by Vapnik [14] et al on the basis of statistical learning theory in 1995.It has obvious advantages in solving the problems of classification recognition and regression prediction, especially in dealing with linear separable optimal classification surface. The basic idea of support vector machine classification algorithm is to find a hyperplane in space that can separate all data samples and maximize the distance between sample data points and hyperplanes. As shown in Fig.10, the solid circle and the hollow circle in the figure represent two kinds of samples to be classified. H is the classification plane. H1 and H2 represent the nearest samples to the classification plane and parallel to the classification plane, the distance Δ between them is called the classification interval.

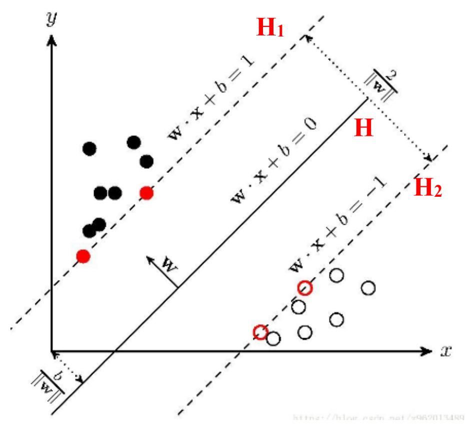


Fig. 10. Linear separable SVM schematic.

Support vector machine was first used to deal with linear separable optimal classification surface problem. In the case of linear separability, the equation of classification surface is $g(x) = w \cdot x + b$, which is normalized so that the nearest sample from the classification surface is $|g(x)| = 1$.At this time, the distance from all points on the H_1 and H_2 planes to the classification plane H is $1/\|w\|^2$ and the classification interval $\Delta = 2/\|w\|^2$,The maximum classification interval is equivalent to the minimum value of $\|w\|^2$,In addition, for the linearly separable training sample set (x_i, y_i), i=1...n , $y \in \{-1,1\}$,must satisfy (8):

$$y_i[(w \cdot x_i) + b] \geq 1, i = 1,2....,n \tag{8}$$

The classification surface that can minimize the value of $1/2\|w\|^2$ while satisfying (8) is called the optimal classification surface, while all sample points on the two sides of the classification plane H_1 and H_2 are called support vectors. This optimal classification surface can separate the two types of samples.

The formula for solving the linear optimal classification surface is shown in (9).

$$\begin{aligned} &\min \quad \varphi(w) = \frac{1}{2}\|w\|^2 \\ &S.t. \quad yi[(w \cdot xi) + b] \geq 1, i = 1,2...l \end{aligned} \tag{9}$$

By introducing Lagrange function to solve the problem, the optimal linear separable classification function can be obtained as follows((10)):

$$f(x) = \operatorname{sgn}\{(w^* \cdot x) + b^*\} = \operatorname{sgn}\left\{\sum_{x_i = sv} a_i^* y_i(x_i \cdot x) + b^*\right\} \tag{10}$$

Where $w*$ is the weight coefficient vector of the classification surface equation; $b*$ is the mean of the support vector of any set of positive and negative samples in the sample; a_i represents the Lagrange multiplier corresponding to each sample and the multiplier a_i which is not zero is recorded as a_i*.

B. *Detection Process*

The main steps of the support vector machine-based image fire detection algorithm adopted in this paper are as follows:

1) Read images.

2) The motion region is extracted by frame difference method and used as fire suspected area, and then preprocessed.

3) Resampling for the same size, extracting flame features including H component first moment feature, texture feature, color moment feature, etc.

4) Normalize the extracted data to get the eigenvector.

5) Using the support vector machine model which trained before to judge.

Fig.11 is the flow chart of image fire detection algorithm based on support vector machine.

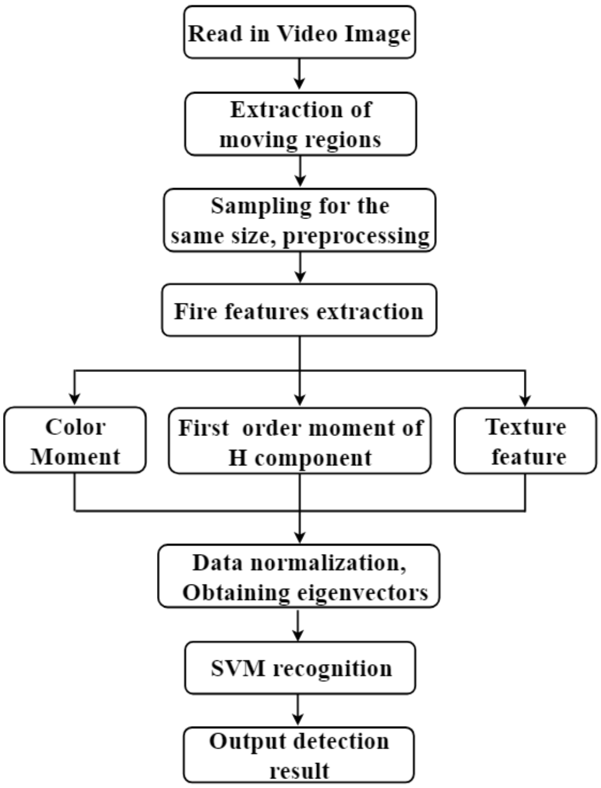


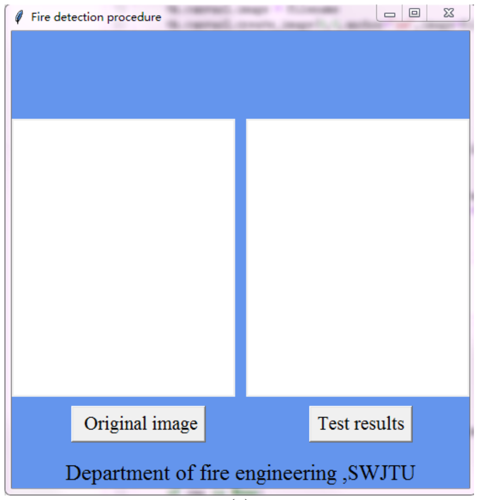
Fig. 11. Flow chart of fire detection.

C. *Setting up Data Set*

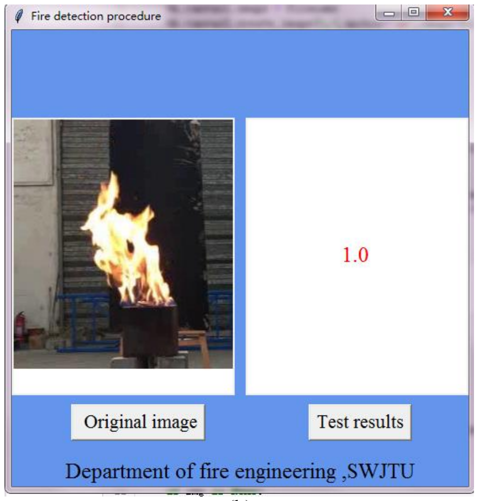
There are 1500 images in this data set, including 1000 positive samples and 500 negative samples. The sources of data set consists of four parts: self-shooting part, ImageNet image database [15], CVPR laboratory data set of Qiming University in Korea [16], and other Internet resources. The image samples were divided according to training set (80%) and test set (20%).

D. *Simulation Results*

According to the algorithm flow of image fire detection based on support vector machine proposed in this paper, Python language is used to program and realize the small program of fire detection. Its interface is shown in Fig.12.The left canvas is used to display the image to be detected; the left canvas is used to display the detection results, 1 represents the fire image, 0 represents the non-fire image.



(a)



(b)

Fig. 12. Fire Detection Program Interface. (a) Detection interface. (b)Detection result.

The algorithm is tested by the test set in the data set, the results show that the accuracy of the algorithm can reach 83%. The specific test results are shown in Table I.

TABLE I. TEST RESULTS

Test Result Table	**Sample types**			
	Positive sample	***Negative sample***	***Total***	***Correctness rate***
Frames	200	100	300	83%

V. CONCLUSION

In this paper, an image fire detection algorithm based on support vector machine was proposed. Firstly, the motion region is detected by the inter-frame difference method and regarded as the fire suspected area. Then the fire suspected area is re-sampled by scene classification method. Next extracting the texture feature and color moment feature of the fire suspected area. Finally, these eigenvalues are input as eigenvectors into the trained machine learning model support vector machine for fire and non-fire classification and recognition. The experimental results showed that the proposed algorithm in this paper can avoid the disadvantage of artificially setting the threshold of flame characteristics and have better accuracy than the typical flame detection algorithm. However, there are some missed or misjudged phenomena. The algorithm does not take into account the dynamic features of flame frequency, circular degree, area change rate, etc. In the future, we can consider improving and optimizing the algorithm from this aspect.

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