RESEARCH ON COALMINE SAFETY MONITORING ACTION RECOGNITION SYSTEM BASED ON KERNEL FUNCTION METHOD

[1]CHAOYU YANG, [2]GANG HE, [3]HUIZONG LI, [4]XIANGQIAN WANG

[1,2,3,4] School of Economics and Management, Anhui University of Science and Technology, Anhui, China
Email: [1]yangchy@aust.edu.cn, [2]hgang0111@163.com, [3]lihz_aust@sina.com, [4]xqwaust@163.com

Abstract - This paper proposed an application solution for the intelligent identification system of coal mine safety monitoring action based on kernel function. We used the object detection model based on kernel density estimation for dynamic background segmentation, combined the adaptive update strategy to extract the foreground moving object. We implemented a method of action feature classification based on SVM model based on mixed kernel function and optimized the model parameters. This paper achieved the coal mine safety monitoring intelligent recognition system framework, provided a solution for intelligent mine monitoring information management, improved the efficiency of coal mining intelligent monitoring management. We could find the hidden danger of safety in coal mine production effectively and timely, and reduced the probability of the occurrence of coal mine safety accidents.

Keywords - Coal mine safety, Intelligent monitoring, Behavior recognition, kernel function; SVM.

I. INTRODUCTION

The coal mine work environment is extremely bad, the accident rate has remained high. The main reason is that the coal mine production safety management measures are not perfect, and the quality of the relevant staff needs to be improved. The main reason is that the coal mine production safety management measures are not perfect, and the quality of the relevant staff needs to be improved. Therefore, strengthening the safety production supervision and establishing the safety awareness of the relevant staff is a fundamental way to effectively control the coal mine safety accidents.

II. ADAPTIVE KERNEL DENSITY ESTIMATION MOTION DETECTION

2.1. Moving target detection based on adaptive kernel density estimation

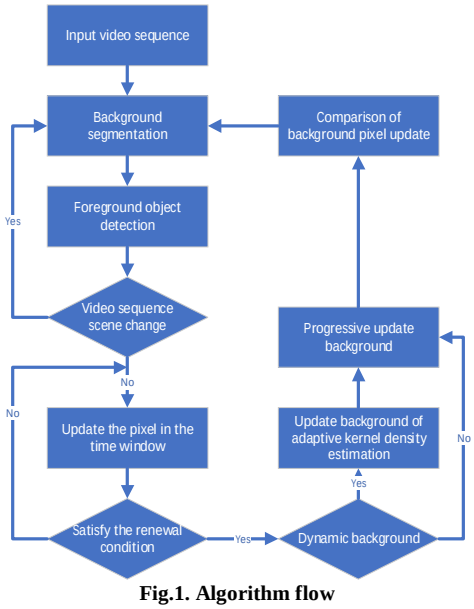


Fig.1. Algorithm flow

In this paper, a kernel density estimation foreground detection algorithm based on pixel time information window is proposed. This method maintains a time information window for each pixel, and uses the non-parametric kernel density estimation to update the dynamic background area that meet the condition. In the process of updating, the hypothesis test is introduced to judge the distribution of the sample and select the kernel width adaptive.

The background area that satisfies the non-dynamic background area update conditions is updated in a gradual way. At the same time, the background mutation of the segmented foreground frames is judged. If there is a mutation in the background, the background is re-initialized. The whole system framework is shown in Figure 1.

2.2. Non-parametric kernel density estimation detection method

Each pixel value in a video sequence can be regarded as a random process. Because of the complexity of mine underground video scenes, the distribution of background density can not be completely described by a single modal model, and the background distribution can not be assumed in advance. Therefore, the kernel estimation method using the video data to get the background model is very suitable for the analysis of the underground mine vision problems with unknown density distribution.

There are M pixels in the video frame, and each pixel has N background samples. Then the pixel value of the i-th pixel is $x(t)_i$ at the time t, and the pixel value which corresponding to the j-th background sample pixel is $x(t)_{i,j}$. The probability $p(x(t)_i)$ of pixel i at the time t can be estimated by the next formula.

$$p(x(t)_i) = \frac{1}{N}\sum_{j=1}^{N} K(x(t)_i - x(t)_{i,j}) \quad (1)$$

K is a kernel estimator, assuming that K obeys normal distribution. For RGB images, R, G and B components can be taken as eigenvalues. If they are independent of each other, the sum of probability of n samples is.

$$p(x(t)_i) = \frac{1}{N}\sum_{j=1}^{N}\prod_{m=1}^{d}\frac{1}{\sqrt{2\pi}\sigma_{i,m}} e^{-\frac{(x(t)_{(i,m)} - x(t)_{(i,m),j})^2}{2\sigma_{i,m}^2}} \quad (2)$$

In the above formula 2, d is the feature dimension of the pixel, and $x(t)_{(i,m)}$ is the m-th eigenvalue of the i-th pixel, and $\sigma_{i,m}$ is the kernel width of the m-th feature. If the probability obtained by formula 2 satisfies the formula 3,

$$p(x(t)_i) < T_f \quad (3)$$

then $x(t)_i$ is the foreground object, in which, T_f is the global threshold under the whole image.

2.3. Adaptive kernel width selection

The variation range of sample values is greater explain that each sample should contribute to the overall density distribution in a larger range. The kernel function should have a larger kernel width, on the contrary, the variation range sample value is smaller, each sample should contribute to the overall density distribution in a smaller range, the kernel function should have a smaller kernel width.

In document 8, a method of calculating kernel width by using the median of absolute difference (MAD) of adjacent samples is proposed. The calculation formula is as follows:

$$\sigma = \frac{m}{0.68\sqrt{2}} \quad (4)$$

In the dynamic background area, when the distribution of the background pixels along the time axis is not normal distribution, it is better to use formula 4 as the kernel width estimation. But in most cases, the background pixels of the non dynamic background area are normally distributed along the time axis. At this time, the estimation of kernel width by sample variance is the optimal estimate.The sample variance x can be obtained by the following formula.

$$\sigma^2 = \frac{1}{N\text{-}1}\sum_{i=1}^{N}(x_i - \overline{x})^2 \quad (5)$$

2.4. Adaptive background update strategy

In the coal mine environment, the scene of the image sequence will change obviously, in which the moving of the background object is more obvious. The background image changes with the light and is confused with the emerging foreground objects. When the background changes, the background model needs to be modified.

In order to update the background model, the proposed strategy is to set up a time window for each pixel in the image, used to record the following information, n sampling value recently , the ratio of foreground pixels F_f , duration T_f of the state of observation, the duration T_g of the pixel did not change , the time interval T_u of the observation state that do not need to update.Among them, the ratio of the foreground pixels refers to the proportion of the number of times that are judged to be a foreground pixels in the N sampling value. The parameters of time information window size according to the specific experimental environment, such as high speed environment if the moving object with fast moving speed, the duration T_f of observation state pixels and the time interval of T_u of the pixels do not need to update should be smaller. In contrast, if in the object moving slowly, the duration T_f of observation state pixels and the time interval of T_u of the pixels do not need to update should be set up greater.

2.4.1. Adaptive updating strategy for non dynamic background region

We let $I_C(i), I_B(i)$ are the pixel value of i, respectively for the current frame and background frame, use the related information of the current frame and background frame to calculate the pixel of successive frames without change by the following formula.

$$T_g(i) = \begin{cases} T_g(i)+1, & |I_c(i) - I_B(i)| < T \\ 0, & \text{other} \end{cases} \quad (6)$$

Among them, $T_g(i)$ is the number of frames that i-th pixel does not change, threshold T is determined by the noise of the image. When the frame count $T_g(i)$ satisfies the formula 7, we consider the background didn't change, and need to update the background pixel value of the corresponding position progressive. α is the update rate in the formula.

$$I_B(i) = \begin{cases} (1-\alpha)I_B(i) + \alpha I_c(i), & T_g(i) = T_g \\ I_B(i), & \text{other} \end{cases} \quad (7)$$

As we update the pixel non dynamic background region gradually, effective to solve the problem of the global noise and shadow and background local pollution caused by moving object into and out from the scene when the illumination changes. At the same time, we avoid the problem of updating the foreground object to the background when the background is updated quickly.

2.4.2. Adaptive updating strategy of dynamic background area based on time window

The non parametric kernel density estimation can solve the problem of background objects change to foreground objects, and foreground objects change to background objects. But in the learning phase, we will take the video sequence pixel value as the sample directly. In practical application, learning video sequences with moving objects. This method calculates the value of the foreground object as the background point, leading to the mistakes of the foreground pixel in the background sample. At the same time, each pixel is calculated by kernel density estimation, which makes the estimation stage with large amount of computation and poor real-time performance. It also easily leads to the error of the non-typical motion pixel estimation and produces a lot of noise.

In this paper, the time window of the pixel is used to update the dynamic background area in real time. When $F_f > A$, the pixel point is in the state of observation S_v, and the pixel point value presents a large fluctuation at this time. It needs observation further, and the model stops updating. If the duration of the state T_f is greater than the set interval T_u, we can decide whether the brightness changes or move in and out the new objects. According to the latest n sampling value, X_1, X_2, X_3, ...X_n, updating the background model with formula 1, when the background changes. The threshold A is set by the object value of the image segmentation.

The adaptive background model updating algorithm can determine whether the background model needs to be updated according to the dynamic information of the pixel points along the time axis. The moving objects can be segmented from the background by using the adaptive background model.

III. FEATURE CLASSIFICATION OF SUPPORT VECTOR MACHINES BASED ON MIXED KERNEL FUNTION

3.1. SVM

Support vector machine (SVM) is a data mining method based on statistical learning. SVM can deal with many problems such as regression problem, pattern recognition and so on, and it can be extended to the fields of prediction and comprehensive evaluation. The mechanism of SVM is to find an optimal classification hyperplane satisfying the classification requirements, which enables the hyperplane to maximize the blank area on both sides of the hyperplane while ensuring the accuracy of classification. In theory, support vector machines can achieve the optimal classification of linear separable data. The problem of constructing the optimal hyperplane is transformed into a constrained solution.

$$\min \Phi(w) = \frac{1}{2}\|w\|^2 = \frac{1}{2}(w' \cdot w) \qquad (8)$$

In order to solve the problem of constrained optimization, the Lagrange function is introduced. The two-time programming problem is transformed into the corresponding dual problem.

$$\max Q(a) = \sum_{j=1}^{l} a_j - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} a_i a_j y_i y_j (x_i \cdot x_j) \quad (9)$$

The optimal weight vector w^* and the optimal bias b^* are calculated, respectively.

$$w^* = \sum_{j=1}^{l} a_j^* y_j x_j \quad (10)$$

$$b^* = y_i - \sum_{j=1}^{l} y_j a_j^* (x_j \cdot x_i) \quad (11)$$

In the formula, the subscript $j \in \left\{ j \mid a_j^* (x_j \square x_i) \right\}$. Therefore, the optimal classification of hyperplane $(w^* x) + b^* = 0$ is obtained, and the optimal classification function is as follows:

$$f(x) = \operatorname{sgn}\left\{(w^* \cdot x) + b^*\right\}$$
$$= \operatorname{sgn}\left\{\left(\sum_{j=1}^{l} a_j^* y_j (x_j \cdot x_i)\right) + b^*\right\}, \quad x \in R^n \quad (12)$$

For linear inseparable cases, the main idea of SVM is to map the input vectors to a high-dimensional feature vector space, and construct the optimal classification plane in the feature space.

We transform the x into Φ from the input space R^n to the feature space H.

$$x \to \Phi(x) = (\Phi_1(x), \Phi_2(x), \cdots, \Phi_l(x))^{\mathrm{T}} \quad (13)$$

By replacing the input vector $\Phi(x)$ with the feature vector x, the optimal classification function can be obtained.

$$f(x) = \operatorname{sgn}\{w \cdot \Phi(x) + b\} = \operatorname{sgn}\left\{\sum_{i=1}^{l} a_i y_j \Phi(x_i) \cdot \Phi(x) + b\right\} \quad (14)$$

The acquired feature vectors are introduced into the support vector machine for training and behavior classification.

3.2. SVM model construction based on mixed kernel function

In machine learning, the classification ability and generalization ability of a classifier are a pair of factors that restrict each other. In the high dimensional feature space, the distribution of the samples will be uneven, and the processing results obtained by the mononuclear kernel function mapping transformation will not be very good. The SVM model of the mixed kernel function which is mixed by the kernel function can give consideration to two aspects of performance. Based on the Gauss kernel function and polynomial kernel function as the

basic function, a new stationary hybrid kernel function SVM model is constructed.

$$K_{mix} = t\exp\left[-\frac{\left|x_i - x_j\right|^2}{2\sigma^2}\right] + (1-t)\left[(x_i x_j) + c\right]^d \quad (15)$$

According to the properties of convex combinations of general kernel functions, the mixed kernel function can satisfy the Mercer condition, which ensures the feasibility of the mixed kernel function.

3.3. Optimization parameters of mixed kernel function SVM

The selection of kernel function related parameters will have a direct impact on the performance of machine learning methods. By adjusting the parameters based on the mixed kernel function, we can bring the parameters into the classifier model, and get different kinds of mixed kernels to generate a new support vector machine algorithm based on kernel function. The performance of SVM is controlled by the parameters in the mixed kernel function and the weight coefficient of the mixed kernel function.

3.3.1. Mixed kernel function parameter

The Gauss kernel function is selected as one of the mixed terms in the mixed kernel function. From the expression $K(x_i, x_j) = \exp\left[-\frac{\left|x_i - x_j\right|^2}{2\sigma^2}\right]$ of Gauss kernel function, we can get that Gauss kernel function separability. According to the separability of Gauss kernel function, for the expression of Gauss kernel function, when $\delta \to 0$, all training samples are support vectors. For any given training sample set S, as long as δ value is sufficiently small, Gauss kernel support vector machine must classify it correctly. But it is easy to overmatch, making the generalization ability of the classification hyperplane decrease. When $\delta \to \infty$, all the sample points will be identified as the same category, so the selection of parameter σ has a great influence on the performance of support vector machine.

If $\gamma = \frac{1}{2\sigma^2}$, Gauss's kernel parameter γ will also affect the performance of SVM. By studying the properties of Gauss kernel function support vector machine, we can get the rule of parameter γ to improve the accuracy of classification and recognition.

Polynomial kernel function is another hybrid term selected by constructing the mixed kernel function. The expression of polynomial kernel function is $K(x_i, x_j) = \left[(x_i x_j) + c\right]^d$, where d is polynomial. When the number of samples and the intermediate d are not too small, the dimension $n_H = n^d$ of the polynomial space H will become larger after the transformation. For example, when n=300, d=5, the dimension can reach hundreds of millions of levels, the calculation of the inner product will inevitably lead to the so-called "dimension disaster". Therefore, the proper order of d is also necessary to improve the accuracy of classification.

3.3.2. Weight coefficient of mixed kernel function

In this paper, the expression of the mixed kernel function is selected as $K_{mix} = t\exp\left[-\frac{\left|x_i - x_j\right|^2}{2\sigma^2}\right] + (1-t)\left[x_i x_j + c\right]^d$, in which t is the weight coefficient of the mixed kernel function, $t \in [0,1]$.

When $t \to 0$, polynomial kernel function has a greater impact on the mixed kernel function, showing the global generalization performance of polynomial kernel function. When $t \to 1$, the Gauss kernel function has a greater impact on the mixed kernel function, showing the local fitting performance of the Gauss kernel function. When the weight function is not selected correctly, the performance of the hybrid kernel function is not as good as that of the support vector machine based on the single kernel function, which will lead to the vanishing of the mixed kernel function. Therefore, the parameters of the nuclear coefficient must be properly optimized.

IV. RESULTS AND DISCUSSION

In the experiment, we decompose the coal mine monitoring data into a frame. For each frame, we detect objects by using the method of kernel density estimation based on the time window, identification of foreground objects. Then, the recognition feature is calculated by using the support vector machine SVM based on the mixed kernel function. Figure 2 shows the recognition and calculation of the characteristic images of the target people in the downhole work. Figure 2A shows the identification of the object people when they work in the underground tunnel, and figure 2B shows the calculated feature images.

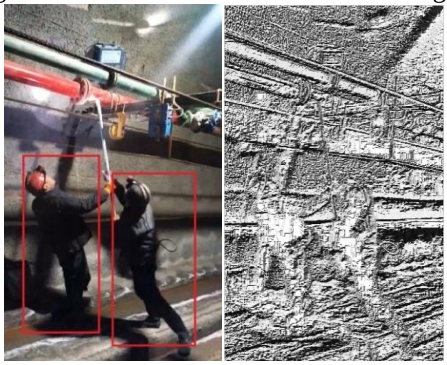


Fig.2. Object action recognition and feature image.

The accuracy of the comparison of the SVM classification of mixed kernel function and the classification of mononuclear SVM is shown as shown in the following table.

Table1: Comparing the results of different models

Single kernel		mixed kernel
Gauss kernel parameter	Polynomial kernel parameter	Mixed kernel parameter
0.556	0.556	3.654
1.254	1.254	0.845
97.445	97.698	99.947

In the video data, we compare the action recognition rate of the method proposed in this paper with the action recognition rate of common method, including BP artificial neural network, K-Nearest Neighbor, gauss mixed model, SVM. We can see the action recognition rate of the method is higher than other common methods apparently.

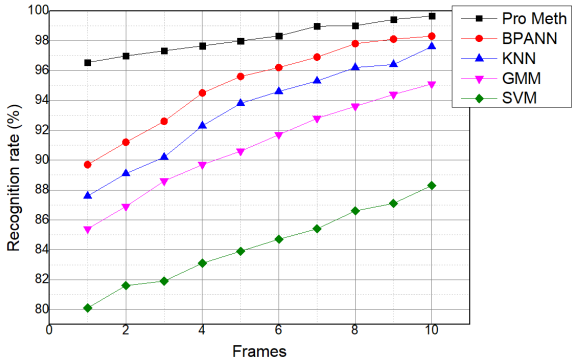


Fig.3. Recognition Rate of Different Actions.

the experiment classified 100 images, judged object action features, compared the consumption time of proposed algorithm and common algorithm. Experimental results are shown in Fig.4.

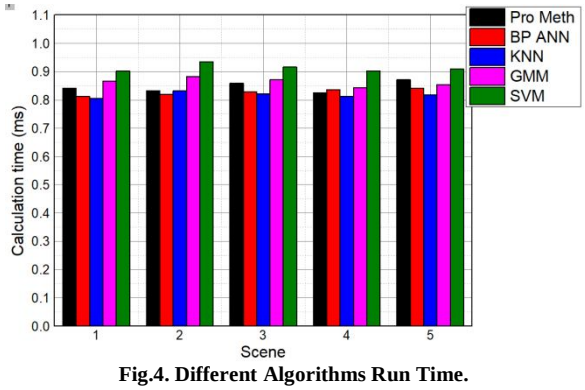


Fig.4. Different Algorithms Run Time.

CONCLUSIONS

Realizing intelligent monitoring of coal mine is an important link of information management of coal mine safety production. This paper provides a kind of information solution for coal mine safety intelligent monitoring. In this paper, an adaptive dynamic object detection model based on kernel density estimation is proposed. We optimize the kernel function parameter and weight coefficient, and design the SVM model by combining the mixed kernel function. At last, we implement the classification of characteristic behavior. Through the implementation of this system, we provide a model basis for the design of coal mine intelligent monitoring system.

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