DE GRUYTER Journal of Intelligent Systems 2024; 33: 20240092

Research Article

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Detection of abnormal tourist behavior in scenic spots based on optimized Gaussian model for background modeling

https://doi.org/10.1515/jisys-2024-0092
received January 31, 2024; accepted June 07, 2024

Abstract: In recent years, tourist attractions have become increasingly popular vacation destinations, leading to a gradual emergence of the tourism market and an improvement in the regulatory systems of scenic spots. However, these attractions frequently experience various abnormal behaviors (ABs). The existing abnormal behavior detection (ABD) algorithms are hindered by interference from the scenic area background, resulting in poor identification of ABs. The study proposed a background model constructed by an optimized Gaussian mixture model based on the background subtraction method to eliminate the background interference. Based on this model, an ABD method was established using action data based on spatio-temporal block detection and motion foreground effect map features. Experiments were conducted to train the video clips and action databases to establish the ABD model. In the study, algorithms were tested using computers, and different scenic spots were set up to validate tourists. Three scenic spot scenes with different time and environmental conditions were set up to detect tourist ABD, and the results were compared with different existing anomaly detection algorithms. Research has shown that the area under the receiver operation characteristic curve in outdoor scenes a and c is significantly larger than that in indoor scene b, with areas under the curves of 96.55 and 97.40%, respectively. In two outdoor research scenarios b and c, the area under the curve and equal error rate of the research algorithm (RA) are 88.14, 18.24, 98.12, and 7.55%, respectively, which are significantly better than the two compared algorithms. Although they are 97.31 and 6.29% in scenario a, slightly lower than the 95.18 and 12.69% of the compared algorithms, the expected time is very close to the ideal value, and overall, they have good performance. In addition, the average recognition accuracy of the RA (93.24%) is higher than that of the comparative algorithm (89.32%). The proposed ABD method has shown certain efficiency and accuracy in identifying ABs. It can provide effective decision-making support for scenic area management and has reference significance for improving the safety management quality of scenic area monitoring. By monitoring the AB of tourists, scenic area management personnel can take timely measures to ensure the safety of tourists and the order of the scenic area. In addition, the results of this study not only provide a new approach and method for detecting AB of scenic spot tourists, but also provide valuable reference significance and theoretical contributions in fields such as video surveillance, behavior analysis, and artificial intelligence.

Keywords: Gaussian model, target detection, abnormal behavior detection, background subtraction method, K-means clustering

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1 Introduction

The challenges faced by tourist attraction managers are multifaceted, covering not only the daily trivialities of scenic area operations, but also in-depth considerations for tourist safety, environmental protection, and service quality improvement. During the peak tourism season, tourists exhibit various behaviors within the scenic area, including some abnormal behaviors (ABs) such as littering, damaging public facilities, and climbing without permission. These behaviors not only affect the environment of scenic spots, but may also pose a threat to the safety of tourists themselves. Therefore, management personnel need to develop effective environmental protection measures to reduce the damage of tourist activities to the environment. At the same time, they need to strengthen environmental protection publicity, improve tourists' environmental awareness, enhance tourist satisfaction, and improve service quality and service. Among the potential consequences of undiscovered ABs, AB often comes with certain safety hazards, such as tourists climbing or wading in water without authorization within the scenic area. Second, the AB of some tourists can cause irreversible damage to the scenic area environment, affecting the overall image of the scenic area and the tourist experience. Finally, some serious ABs, such as theft and fighting, not only cause physical and mental harm to tourists, but also have a negative impact on the image and social security of the scenic area, damaging its reputation and image. In order to detect the AB of tourists, object anomaly detection algorithms have been proposed, but existing object detection and recognition algorithms are affected by background interference, resulting in poor recognition performance in video surveillance [1,2]. The high-efficiency and high-precision abnormal behavior detection (ABD) method has reference significance for improving the quality of monitoring and safety management in scenic spots. In order to deal with background interference and improve target recognition ability, a detection target description method combining background subtraction method (BSM) optimized Gaussian model with spatial block detection and motion foreground drawing features is proposed. By monitoring surveillance videos in the area, specific ABs can be identified and warned in real time. However, in practical applications, there may be challenges: in scenic areas, occlusion between tourists and scenic facilities may cause some or all of the target tourists' bodies to be hidden, making it difficult to identify ABs. Second, the complexity of the scenic area environment makes it difficult to accurately update the background model. Lighting conditions may also cause changes in the brightness and contrast of the image. Then, there are various behaviors of tourists in the scenic area, and some ABs may manifest as complex action sequences. In response to these challenges, research can consider adopting more advanced deep learning algorithms to improve the accuracy and real-time performance of ABD. The research structure of this article is as follows: The first section introduces the background, significance, and prospects of AB recognition and detection in tourist attractions. Then, the second part focuses on establishing a background model based on optimized hybrid Gaussian model (GM) and designing the ABD method. The latter is also the focus and innovation of this study. The third part introduces the experimental verification using the model and method developed in the second part, and analyzes the experimental results. The fourth part summarizes the experimental results, discusses the shortcomings and limitations of the design, and outlines the future development direction

2 Related works

In tourism settings, implementing machine learning techniques and behavior recognition technology to identify AB can enhance the supervision system of scenic areas, reduce manpower expenditure, and enhance accuracy and real-time monitoring. Numerous researchers have provided their own research and perspectives regarding this topic. Arisoy and Kayabol proposed an algorithm for hyperspectral image anomaly detection based on nonparametric Bayesian background estimation. They used the Gaussian mixture model (GMM) for estimating parameters and model order of the proposed method for anomaly detection. It is shown that the detection performance of the method outperformed other methods on real hyperspectral datasets [3]. Dongling et al. proposed a GM-based adaptive update template defect enhancement algorithm. It has been demonstrated that the accurate localization of flaws was attained, effectively enhancing contrast and removing noise effects [4]. Cai and other researchers presented a shared state space model employing two recurrent neural networks to extract the background information and the temporal properties of the target sequence by adding a shared background information component to the state space model. The information that was retrieved was included in the state space model as linear Gaussian components, and a Kalman filter was used to perform the inference procedure. The model log-likelihood was used to optimize the model. Tests showed that the model beats the most advanced techniques and is able to retrieve the common information hidden in the data [5]. An artificial intelligence and sequence minimization (SMO) algorithm optimization model-based sports combined training behavior recognition model was proposed by Jiang and Tsai. The model lowers the false recognition rate and increases the recognition rate of sports movements, according to test results [6].

Preventing injuries, fatalities, and property damage requires identifying and eliminating ABs that pose a concern to public safety. The goal of numerous research projects has been to create intelligent video surveillance systems that can automatically identify unusual activity by identifying human behaviors. These investigations, however, have concentrated on identifying predetermined activities that are directly associated with the target's AB, which could result in incorrect or missed detection of these acts. A method for identifying anomalous behaviors was put out by Kim et al. using sequence analysis of the identified action components to infer behavioral intent, and deep learning-based identification of non-semantic-level human action components segregated in a few-second timeframe. Through the analysis of real event data, it was determined that intent can be evaluated with accuracy using various action sequence elements. This opens up new avenues for monitoring ABs and getting insight into their intent, ultimately enhancing the capabilities of intelligent surveillance systems [7]. A technique for identifying unusual access behaviors in university civics catechism classrooms was presented by Hong et al. The outcomes demonstrated that the technique may successfully identify unusual access behavior [8]. Wu and Cheng focused on detecting AB of indoor people using a new in-room effective ABD framework to achieve detection of AB of indoor people. Fuzzy C-mean clustering was used to detect outliers in the data samples. Experimental studies showed that the detection framework has good practical application value [9]. Aiming at the problem of low performance of crowd ABD due to complex background and occlusion, Song and Sheng proposed a single-image crowd counting and ABD method based on multi-scale Generative adversarial network (GAN). An embedded GAN module with multi-branch generator and region discriminator was first designed for initial generation of crowd density map. Then, the proposed multi-scale GAN module was added to obtain crowd motion trajectories using synthetic optical flow feature descriptors to achieve AB classification. The technique can considerably increase the robustness and accuracy of crowd counting and ABD in real complicated scenarios, according to simulation studies [10].

In order to improve the performance of motion detection, Zheng et al. proposed a Gaussian modeling algorithm to repair holes and fractures caused by traditional frame difference methods. The proposed algorithm uses an improved three frame difference method and sets a threshold to predict the results used to obtain the accuracy of moving object detection. The experimental results show that the algorithm can suppress the generation and rupture of holes, reduce noise, and quickly and accurately detect motion [11]. The traditional theory of motion target detection has drawbacks such as clustering, background updating, inaccurate detection results, and low anti-interference performance. Hu and Xu used background subtraction to automatically capture the basketball shooting trajectory, improving the accuracy and efficiency of motion target detection. The results show that compared with the inter frame subtraction method (88%) and the optimal flow method (85%), the background subtraction method has better accuracy, with an accuracy rate of over 90%, and has good robustness when considering variable speed and non-rigid objects [12]. The AB of the abnormal population has significant variability, as well as significant ambiguity and uncertainty in video content. Li et al. proposed a new probabilistic framework called Variational ABD (VABD). The experimental results show that VABD is superior to state-of-the-art algorithms in detecting abnormal crowd behavior. Without increasing data, the area under the curve (AUC) of VABD on the IITB corridor reached 72.24%, which is nearly 5% higher than the state-of-the-art methods [13]. IITB Carrier is a large-scale surveillance dataset containing 4.83566 frames of video data, provided free of charge for research purposes, particularly for evaluating existing technologies for anomaly activity detection tasks.

In summary, researchers have examined data recognition and algorithm classification for AB recognition and detection. However, more in-depth work is needed to enhance the GMM, eliminate background interference, and improve the efficiency of AB recognition. The study suggests an optimized GMM which utilizes BSM and K-means clustering to establish a background model. Additionally, it merges the spatial time block detection and motion of ABD recognition method of the foreground effect map to detect AB among scenic tourists. The outcome of this research would provide a technical foundation for the safety monitoring and management of scenic spots.

3 Background model and ABD method based on optimized Gaussian model

Efficient and controllable ABD methods can improve the efficiency of scenic area supervision and promote safety management. Identifying ABs of tourists through video surveillance is the main way of safety management in current scenic spots, which can directly reflect the behavior of tourists in scenic spots [14]. The research constructs a background model based on optimized GM to solve the interference of scenic background on the algorithm of identifying ABs, to improve the accuracy and efficiency of identification, and designs a new ABD method combining the spatial time block and motion effect feature map.

3.1 Hybrid Gaussian background model based on K-means clustering optimization

In recent years, with the increasing number of stampede incidents among tourists in scenic areas, large-scale crowd behavior analysis has become a research hotspot in the field of video surveillance. The existing anomaly detection algorithms have poor recognition performance due to the interference of scenic background. The dynamic changes and complexity of the scenic environment, such as weather changes, light and shadow changes, and changes in pedestrian flow, may make it difficult to accurately update the background model. For example, the dynamic process of tourists gathering and dispersing, or the continuous changes in natural elements such as trees and water surfaces, may interfere with the background model. Lighting conditions are a very important influencing factor in the environment of scenic spots. The lighting conditions vary greatly at different times, seasons, and weather conditions, which may lead to changes in the brightness and contrast of images, thereby affecting the accuracy of anomaly detection. Therefore, based on the background subtraction method, a background model optimized by GMM is proposed to eliminate background interference. As a commonly used motion target detection method, BSM is an inter-frame differencing method that utilizes a background model to update the background image, which is obtained by differencing the background image from the main object, with the advantage of being sensitive to the background and speeding up the computation. Figure 1 displays the BSM schematic diagram.

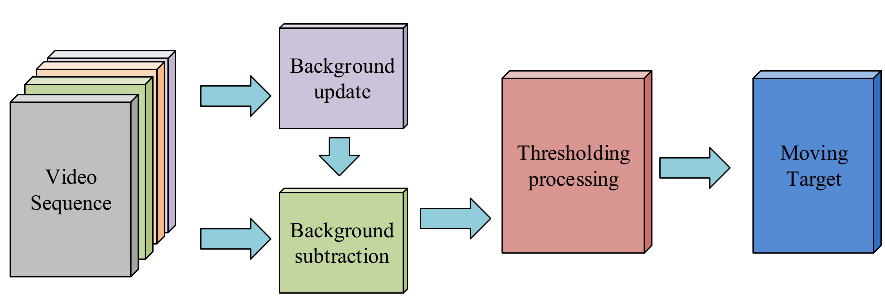

Figure 1: Schematic diagram of BSM.

The image is binarized according to BSM as in equation (1).

$$\begin{cases} |I_f(x,y) - I_{bk}(x,y)| = D_k(x,y) \\ R_k(x,y) = \begin{cases} 0, D_k(x,y) < T \\ 1, D_k(x,y) \geq T. \end{cases} \end{cases} \quad (1)$$

where $I_{bk}(x,y)$ is the background image, $I_f(x,y)$ is the current frame image, $D_k(x,y)$ is the difference image, $R_k(x,y)$ is the binarization result, and T is the binarization setting threshold. GM is divided into two types according to the background model, i.e., unimodal and multimodal, and unimodal is used for the background image when the gray scale distribution is concentrated, and multimodal is used for the more dispersed time [15]. The unimodal GM and hybrid multimodal GM distribution curves are shown in Figure 2.

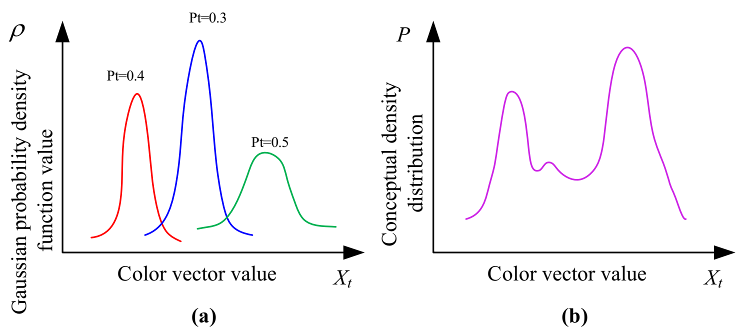

Figure 2: The unimodal GM and hybrid multimodal GM distribution curves. (a) Single Gaussian model distribution curve and (b) multimodal Gaussian model distribution curve.

In Figure 2, the single Gaussian distribution model curve disperses with different parameters and cannot fit well with the pixel distribution model. The mixed Gaussian distribution model combines the properties of a single Gaussian distribution model and has robust and real-time detection effects. Due to the complexity of the background in scenic areas and the uneven grayscale distribution, the study used mixed Gaussian for background modeling. The hybrid GM is modeled as in equation (2).

$$P(X_t) = \sum_{i=1}^{K} w_{i,t} \cdot \rho\left(X_t, \mu_{i,t}, \sum_{i,t}\right), \quad (2)$$

where K denotes the number of Gaussian distribution (GD), $w_{i,t}$ denotes the ith GD weight at the moment of t, $X_t = (x_t^r, x_t^g, x_t^b)^T$ denotes the color vector value of the pixel point at the moment of t, $\mu_{i,t}$ denotes the mean vector of the ith GD at the moment of t, $\sum_{i,t}$ denotes the covariance matrix of the ith GD at the moment of t and $\sum_{i,t} = \delta_n^2 I$, I denotes the unit matrix [16]. If the three components of the image R, G, B are independent of each other, then the Gaussian probability density function is as in equation (3).

$$\rho\left(x_t, \mu, \sum\right) = \frac{1}{(2\pi)^{n/2}|\sum|^{\frac{1}{2}}} e^{-\frac{1}{2}(X_t-\mu_t)^T \sum^{-1}(X_t-\mu_t)}, \quad (3)$$

where ρ denotes the Gaussian probability density function and n denotes the pixel component dimension with a value of 3. The GM first needs to perform parameter updating at the time of foreground target extraction to estimate the GD that represents the background as well as the motion target segmentation [17]. The algorithm flow is shown in Figure 3.

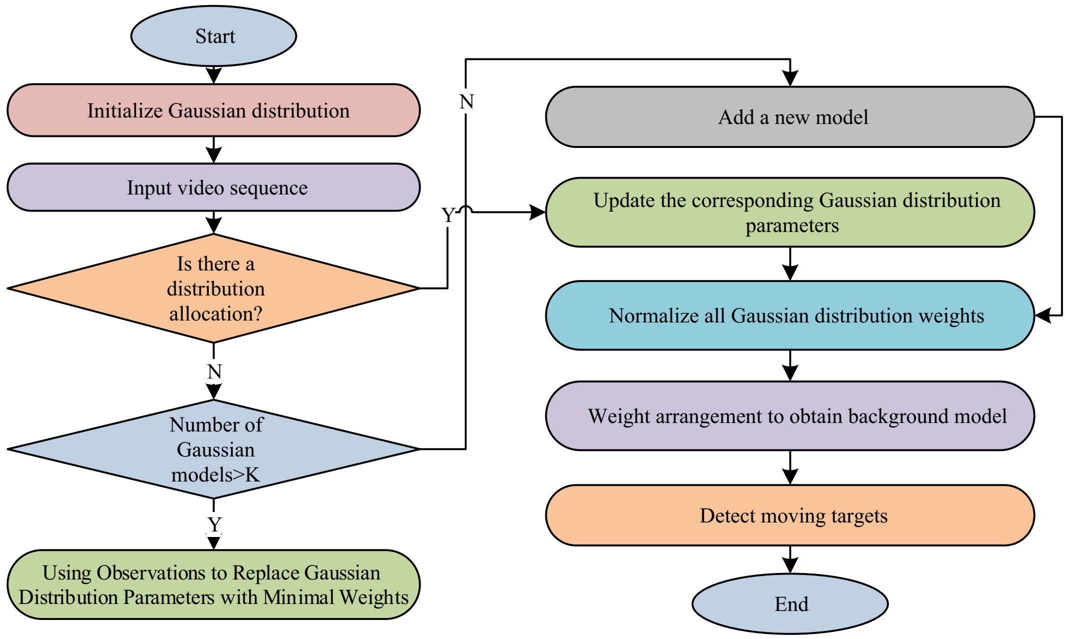

Figure 3: Algorithm flowchart of mixed Gaussian model.

3.2 Optimization of GMM based on K-means clustering

In Gaussian background model, background training of Gaussian background model is required, but human objects are almost always present in many videos and human targets have a great impact on the training of the model, so the study proposes an online K-means clustering algorithm for initialization of GM. This method is able to cluster the image sequence pixel gray values, update the correlation coefficient in the clusters, and construct the GD clustering number, thus improving the speed of the algorithm. The specific optimization process is as follows, first, at the moment $t = 1$, the pixel point (x, y) of the first frame image of a certain video is defined as in equation (4).

$$c_1 = 1, m_1^1 = 1, \mu_1^1 = X_1, BK_1 = 0, \tag{4}$$

where m_t^k denotes the samples in the kth cluster at the kth moment, μ_t^k denotes the mean RGB color vector value, and $BK_t = (bk_t^{k,r}, bk_t^{k,g}, bk_t^{k,b})$ denotes the RGB color vector value of the reconstructed background. Each pixel point's brightness value in the newly collected image frame is categorized according to equation (5).

$$|\mu_{t-1}^{i,t} - x_t| \le \varepsilon, \tag{5}$$

where ε denotes the threshold value that determines whether the pixel point is changed or not. The pixel point is categorized as class i and the update parameters are as in equation (6).

$$\begin{cases} c_t = c_{t-1} \\ m_t^i = m_{t-1}^i + 1 \\ N_{i,t} = N_{i,t-1} + 1 \\ \mu_t^i = \dfrac{\mu_{t-1}^i + m_{t-1}^i + X_t}{m_t^i} \\ \delta_t^2 = \dfrac{[N_{i,t} \cdot (\delta_t^2 + \mu_t^2)]}{N_{i,t}} - \mu_t^2. \end{cases} \tag{6}$$

If the brightness value does not satisfy equation (6), it means that the pixel point does not belong to all the classes set, and a new class needs to be added. Additionally, the new class parameter's starting value is shown in equation (7).

$$\begin{cases} c_t = c_{t-1} + 1 \\ m_t^{\mathrm{new}} = X_t \\ N_t^{\mathrm{new}} = 0 \\ \sigma_{\mathrm{new}}^2 = 0, \end{cases} \tag{7}$$

where σ_t^2 denotes the variance. After X_t clustering is completed, the background pixel points are updated as in equation (8).

$$\begin{cases} j = \arg\max_k \{m_t^k\} \\ BK_k = \mu_t^j, \end{cases} \tag{8}$$

After completing the clustering for each pixel brightness value in the training sequence N frame image, the reconstructed background image was utilized to parameterize the GM according to equation (9).

$$\omega_{i,0} = N_i/N, \mu_{i,0} = BK_t, \sum_{i,0} = \sigma_{i,N}^2 \cdot I, \tag{9}$$

where I denotes that the unit matrix is 3 × 3. In summary, the study used K-means clustering to optimize the Gaussian model and established a background model based on a mixed Gaussian model. I hope to continuously improve the regulatory system for scenic spots in the tourism market, identify various violations and dangerous behaviors, provide important safety management references, and improve timely management efficiency.

3.3 AB recognition of tourists in tourist attractions combined with background models

Tourist attraction is a kind of regional place mainly for tourism and related activities, usually for tourists to visit and tour, vacation, fitness, etc. in their leisure time, but also with related facilities and provide corresponding tourism services in an independent management area [18]. AB refers to an unusual action that occurs in a normal position at a normal moment in a certain scenario, or an action that occurs in a non-normal position at a non-normal moment. The behavior is usually emitted by human beings, including some violent nature behaviors, which usually occur under the condition of more than two people and the action occurs fast, and some other nonviolent nature behaviors, which are usually initiated by one person and the action occurs over a longer period of time. Due to the abovementioned reasons, ABs need to be identified and monitored to provide safety technical support for tourist attraction managers [19]. The study proposes a background model based AB recognition method, and further designs the ABD method by optimizing the background model established by hybrid GM. Deep learning algorithms are excellent algorithms in the field of machine learning, which have significant development prospects in the field of image recognition and speech recognition, and can be used for recognizing pedestrians' ABD, but there may be false detection in a certain frame or multi-frame images, and it may lead to ineffective tracking of the target on the scene with high crowd density, etc. The study proposes a detection target description method combining spatial block detection and motion foreground effect map features based on the background model established based on optimized GM, which is applied to detect tourist crowd ABD.

3.3.1 Description of detection objects in scenic area monitoring

In order to characterize the detected objects in scenic surveillance so as to locate the anomalous objects, the study is carried out in two phases, i.e., global anomaly detection and partial ABD. First, the video frames are viewed as a whole, and only the image frames of the anomalous objects are detected. Then, the video frame is segmented into equal blocks of airtime and the corresponding features are extracted separately to detect the anomaly object. The video frame is split up into several spatial blocks of the same size, using the space-time block as the detection object. Subsequently, the motion foreground effect map feature extraction is executed to derive the feature extraction frame flow, as illustrated in Figure 4.

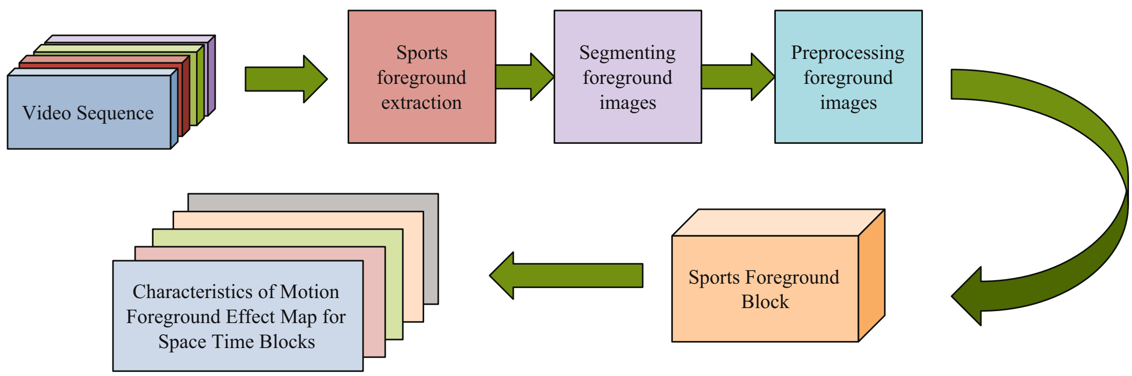

Figure 4: Block diagram of feature extraction for sports foreground effect maps.

The motion foreground block is obtained by first extracting the background region using the optimized hybrid GM, then obtaining the spatial block and foreground image, preprocessing the two to obtain the effect weight vectors, and finally averaging the effect weight vectors to obtain the feature description. The most effective way to analyze AB is to analyze the motion information of moving pedestrians, and generally AB will show a rapid change in the motion information [20]. The background model established by the study based on the optimization GM excludes the influence and interference brought by the scenic background on the motion foreground information, so the study focuses on the tourists' abnormal motion information here. In the extraction stage of the motion foreground block, the null partition model is set, and the conditions for the selection of the motion foreground block are as in equation (10).

$$G_i = B_j, \quad \text{if} \quad \frac{b_j}{L \times L} > \lambda, \tag{10}$$

where b_j denotes the number of foreground points within a block, $G_i(1 \le i \le S)$ denotes that image block B_j can be used as the ith motion foreground block when the condition is satisfied, $L \times L$ denotes the size of each spatial block scale, and λ is the foreground point scale threshold [21]. To describe the motion foreground block, a dense OF algorithm is used to calculate the OF vector of each pixel point of each frame of the original image sequence, which is able to provide an intuitive representation of the motion state. The study takes the average of the OF vectors of all pixel points of the motion foreground block as the current OF vector, as in equation (11).

$$g_i = \frac{1}{J}\sum_j o_i^j, \tag{11}$$

where g_i denotes the OF vector of the ith motion foreground block, J is the all pixel points within that foreground block, and o_i^j denotes the OF vector of the jth pixel point in the ith motion foreground block. The definition of two indicator variables is given in equation (12).

$$\begin{cases} \gamma_{ij}^d = \begin{cases} 1, & \text{if} \quad \text{dist}(i,j) < \delta_\text{d} \\ 0, & \text{else} \end{cases} \\ \gamma_{ij}^d = \begin{cases} 1, & \text{if} \quad -\frac{\pi}{2} < \theta_{ij} < \frac{\pi}{2} \\ 0, & \text{else,} \end{cases} \end{cases} \tag{12}$$

where the angle between the vector from the foreground block to the spatial block and the OF of G_i is represented by θ_{ij}, the distance threshold is represented by δ_d, and the Euclidean distance between the moving foreground block G_i and the spatial block B_i is shown by $\mathrm{dist}(i, j)$ [22]. These two indicator variables quantify whether the spatial block is inside the sphere of impact of the foreground block. And the foreground block motion model is shown in Figure 5.

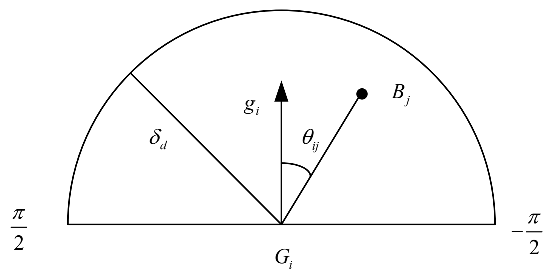

Figure 5: Motion model diagram of foreground block.

The effect weights of the motion foreground blocks on the spatial blocks are calculated as in equation (13).

$$w_{ij} = \begin{cases} \gamma_{ij}^{d}\gamma_{ij}^{\theta}\exp\left(-\dfrac{\mathrm{dist}(i,j)}{\|g_i\|}\right), & \text{if } \; G_i \neq B_j \\ \gamma_{ij}^{d}\gamma_{ij}^{\theta}\exp\left(-\dfrac{1}{\|g_i\|}\right), & \text{else,} \end{cases} \tag{13}$$

where w_{ij} represents the effect weights. There is a change rule between the operation foreground block G_i and space block B_i. Draw the effect weight values of spatial blocks based on the quantization direction of optical flow in the foreground block, as shown in equation (14).

$$\begin{cases} q(\measuredangle g_i) = k_i, & \text{if } \; (k_i - 1) \times \dfrac{2\pi}{p} < \measuredangle g_i \leq k_i \times \dfrac{2\pi}{p} \\ h_j = (k_i) = \sum w_{ij}, & \text{if } \; q(\measuredangle g_i) = k_i, \end{cases} \tag{14}$$

where in order to make the extracted features have a high and strong differentiation, the motion direction $\measuredangle g_i$ of G_i is quantized, p is the total number of quantized direction intervals, k_i denotes the quantized direction index value of the OF of the ith motion foreground block, h_j denotes the histogram statistic, and $h_j \in R^p$. Finally, for the sake of long-time statistics of motion foreground blocks, the computational characterization of the consecutive frames of the spatial block of the null sub-chunks is carried out, and the corresponding motion foreground characterization is shown in equation (15).

$$\hat{h}_j = \frac{1}{\tau}\sum_{i=0}^{\tau-1} h_{j+1}, \quad \hat{h}_j \in R^p, \tag{15}$$

where τ denotes the number of consecutive frames.

3.3.2 ABD based on motion foreground rendering features

On the basis of the above calculation of the features of the foreground effect map of crowd motion, the resulting features are clustered, and the specific process is shown in Figure 6.

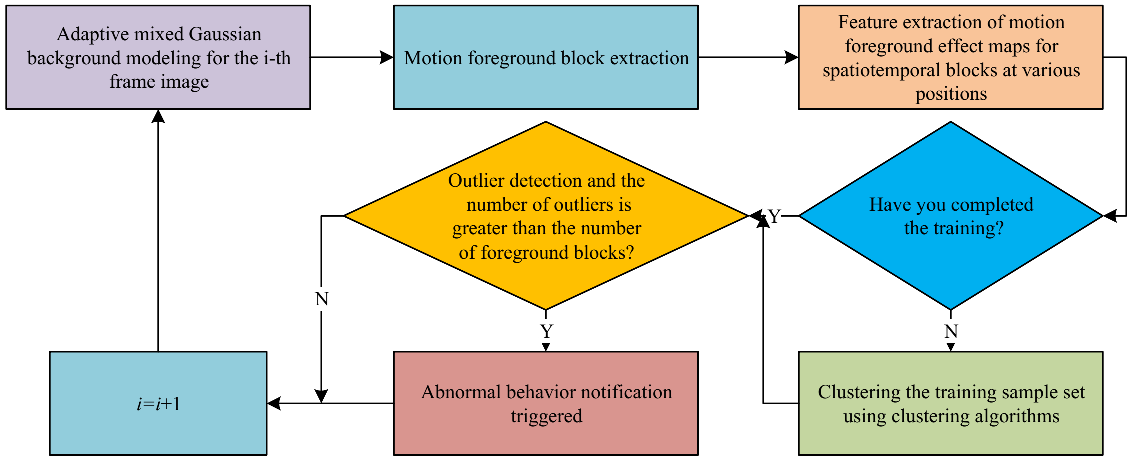

Figure 6: Flow chart for ABD based on motion foreground effect map features.

The study used an improved clustering algorithm with optimized clustering centers for its clustering, first, the mutual distances between all the samples in the sample set were calculated, and the sample point with the largest distance was selected as the clustering center [23–25]. Once the optimal clustering category has been identified, the collection of clustering centers is obtained by extracting the set of feature samples of all airtime blocks using the trained clustering model. After counting the number of abnormal airtime blocks, the AB is found by measuring the distance between the feature samples of the detected airtime blocks and the features of the motion foreground effect map.

4 Validation experiment of ABD method for tourists in scenic spots

An experiment is conducted here to verify the feasibility and benefits of the research-proposed tourists' ABD method, which is based on the background model design of optimized GM. It also provides technical support for the management of people's safety and order in scenic areas. The experiment also analyzes the corresponding design parameters and experimental data results.

4.1 Experimental parameters and process design

The background model constructed based on optimized GMMs and subsequent anomaly detection methods need to consider multiple factors: in terms of computational efficiency, GMM training usually involves a lot of iterations and parameter optimization. By optimizing the algorithm and selecting appropriate initial parameters, training time can be significantly reduced. The optimized GMM and related anomaly detection algorithms should have high computational efficiency. For large-scale datasets or high concurrency scenarios, parallel computing techniques can be used to accelerate processing speed. In terms of resource requirements, in order to train and optimize the GMM model and perform real-time anomaly detection, it is necessary to have certain computing resources to support the required computing load and ensure the stability and reliability of the system. Computers were used in the studies to run the algorithm tests and confirm that the backdrop model created by the optimization GM and the ABD approach for scenic tourists was effective. The computer is configured for Windows, and the CPU is configured for Core™ i7-6400, 12.4 GHZ. The experiments are mainly carried out on the MATLAB 2016 platform, and different scenic spots are set up for the verification of tourist ABD. The data selected for the experiment come from the surveillance video clips of a tourist attraction and the behavioral database provided by a hospital, and the video clips include ten surveillance videos. After preprocessing, the data set the actual specific frame numbers of the anomalous frames in the video, as shown in Table 1. This dataset includes ten video segments covering three scenarios (two outdoor and one indoor, set as a, b, and c, where a and c are outdoor), with a total frame rate of 7,670 and a video frame resolution of 320 × 240. The video frames where the crowd starts to scatter and run are called abnormal frames, and all of these frames are labeled as abnormal frames. The comparison algorithms selected for the study are the existing Histograms of oriented optical flow (HOF), Histogram of maximal optical flow projection (HMOFP), and the corresponding metrics are selected as AUC and Equal error rate (EER).

Table 1: The actual number of abnormal frames in the video

Scene	Video clips	Start frame count	Abnormal start frames	Abnormal end frames	End Frames
Scene a	1	1	429	605	648
	2	659	1,354	1,497	1,508
	3	1,594	1,657	1,988	2,183
Scene b	4	2,247	2,597	2,642	2,719
	5	2,813	3,018	3,294	3,514
	6	3,597	3,829	3,994	4,192
Scene c	7	4,208	4,771	5,001	5,142
	8	5,268	5,499	5,641	5,681
	9	5,920	6,154	6,288	6,905
	10	6,993	7,294	7,730	7,649

The study conducts experiments on the detection and recognition effect of the ABD method based on different behavioral actions of tourists. Based on different types of behaviors set in the behavioral database, such as running, jumping, squatting, falling, wandering, etc., the proposed algorithm is used to conduct behavioral detection of the study, and the related recognition accuracy is recorded.

4.2 ABD data measurement and analysis

The experiment verifies the RA's detection performance in three scenarios and displays the corresponding receiver operation characteristic (ROC) curves, depicted in Figure 7(a). Additionally, the values for the AUC and EER indices are shown in Figure 7(b). In Figure 7(a), the area under the ROC curve in scenarios a and c is significantly larger than in scenario b, corresponding to the AUC of 96.55 and 97.40% in Figure 7(b),

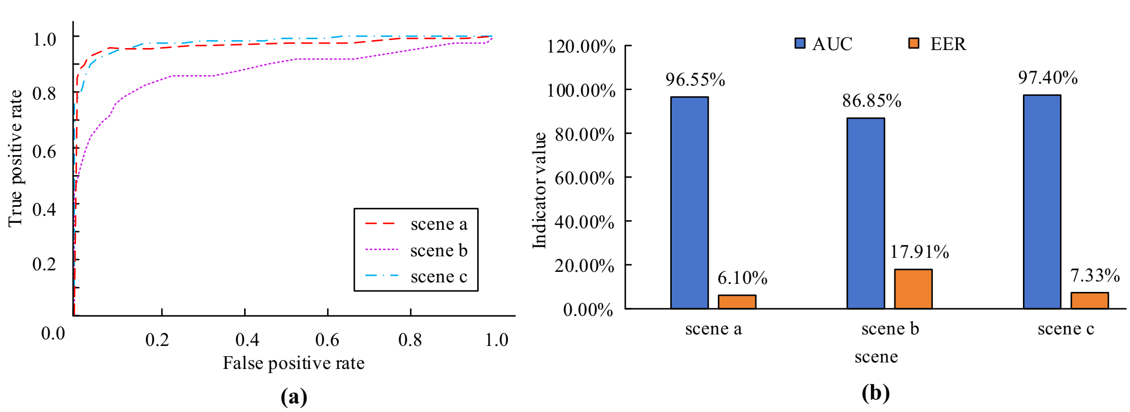

Figure 7: ROC curve, AUC, and EER index values of the proposed algorithm in three different scenarios. (a) ROC curves for in three scenarios of UMN dataset and (b) the AUC and EET indicator values of the proposed algorithm in three scenarios.

respectively. It can be seen that the detection performance in scene a and scene c is better, while the detection performance in scene b is relatively weak, indicating that the research method has better outdoor anomaly detection performance.

Table 2 displays the results of a study conducted to further validate the efficacy of the designed ABD method and examine the impact of various algorithms in various scenarios with varying performance indicators. The indicators were compared with RAs were AUC and EER. The AUC and EER of RA in scenarios b and c are 88.14, 18.24, 98.12, and 7.55%, respectively, which are obviously better than the two algorithms in comparison, although in scenario a, it is 97.31 and 6.29%, which is slightly inferior to the HMOFP algorithm's 95.18 and 12.69%, but it is expected to be very close to the ideal value, and overall has a good performance.

Table 2: Performance indicators of different algorithms in different scenarios

Scene	Evaluating indicator	RAs (%)	HMOFP (%)	HOF (%)
Scene a	AUC	97.31	98.14	95.18
	EER	6.29	6.49	12.69
Scene b	AUC	88.14	85.19	81.57
	EER	18.24	25.36	27.43
Scene c	AUC	98.12	97.45	96.09
	EER	7.55	7.38	7.70

In the experiment, walking is set as normal behavior and others are AB, such as running, bending to walk, and falling. The corresponding data actions are collected for training to obtain the corresponding model. The backgrounds of the three traveling scenes are segmented for recognition and extraction to build the corresponding background models. In addition, the RA and Song proposed a single image crowd counting and ABD method based on multi-scale GAN networks (compared with Algorithm 1), Wu and the team proposed a new indoor effective ABD framework (compared with Algorithm 2), and Jiang et al. proposed an optimized model based on SMO algorithm and an artificial intelligence motion combination training behavior recognition model (compared with Algorithm 3) for recognition accuracy comparison, as shown in Figure 8. It can be seen that the recognition accuracy of algorithms 1, 2, and 3 is generally lower than that of the RA, with an average recognition accuracy of 89.32, 89.80, 88.23, and 93.27%, respectively. When identifying hovering actions, the accuracy of the RA and the comparison algorithm are 87.69, 84.02, 81.47, and 80.16%, respectively. This is because hovering actions are no different from normal actions, except for the length of action

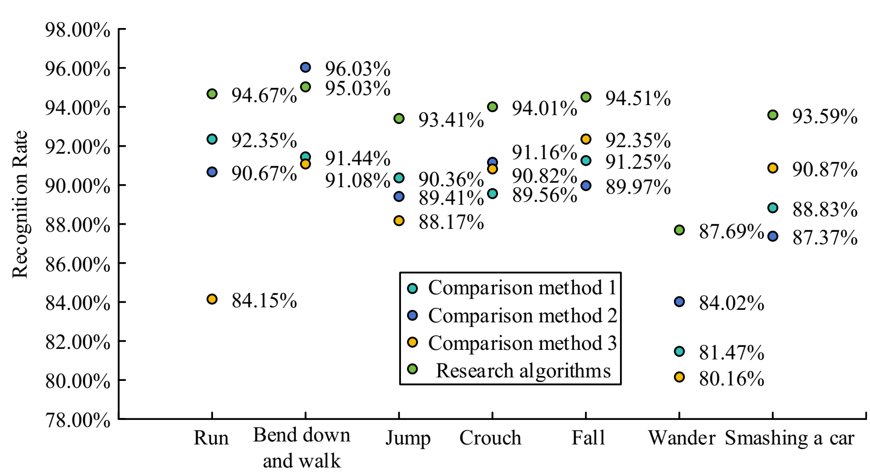

Figure 8: AB identification results.

repetition. It can be seen that the algorithm proposed this time has good accuracy in identifying abnormal actions of tourists.

As shown in Figure 9, in order to visually analyze the different features between AB and normal behavior, the study plotted the feature histograms of the two actions under different mode operators, and the normal behavior study selected the walking action, and AB selected the bending action. The target area contained in the image is relatively large compared to the background area, and there is a certain difference in grayscale between the background area and the target area. The peak in the histogram in Figure 9 is not obvious, indicating that the operator's influence on the reflection of the histogram is not deep. Figure 9(a) and (b) show the histograms of the features of the stooping action under the two modes, and the stooping action shows flatter fluctuations. Figure 9(c) and (d) shows the histogram of the features of the walking action in the two modes, and the performance of the histogram of the features of the walking action fluctuates significantly.

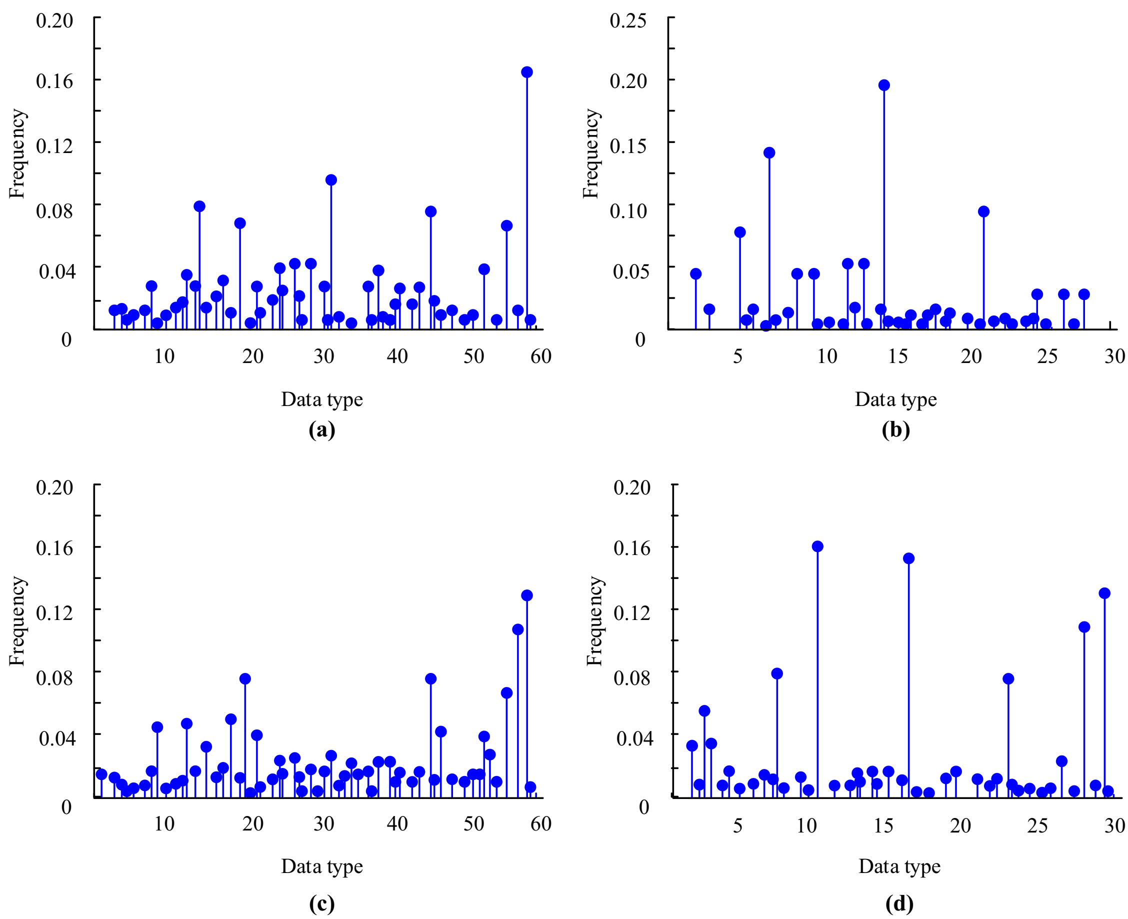

Figure 9: Characteristic histograms of two actions under different mode operators. Histogram of bending behavior in (a) Mode 1 and (b) Mode 2. Histogram of walking behavior in (c) Mode 1 and (d) Mode 2.

Figure 10 shows the aspect ratios of the minimum outer rectangular box obtained by morphological analysis after GMM segmentation of their motion foreground maps for normal walking and running actions under the color model. In Figure 10(a), the change in the aspect ratio of the rectangular box is more balanced and regular in the case of normal walking, and in Figure 10(b), the aspect ratio of the rectangular box in the case of running is a faster change with a short duration.

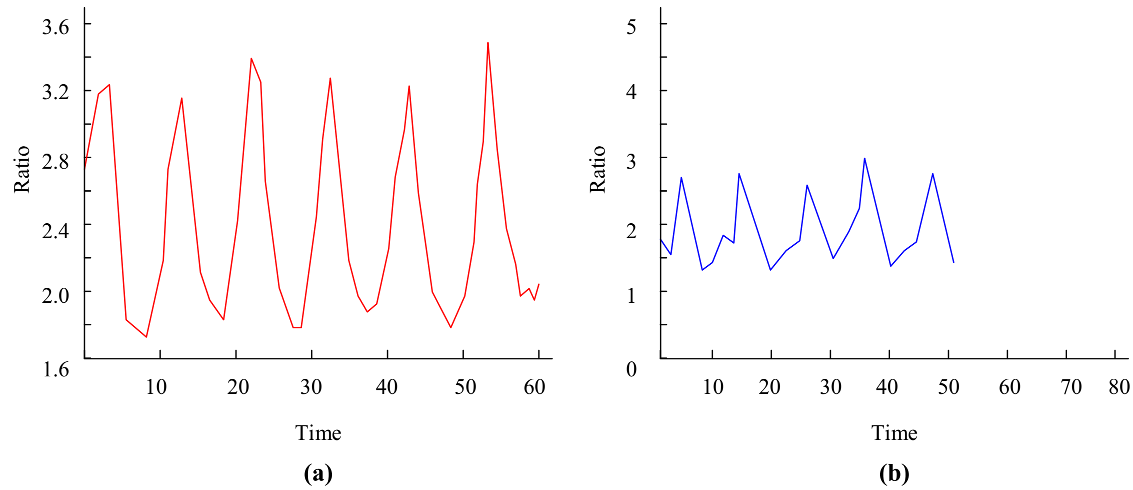

Figure 10: The aspect ratio of the minimum bounding rectangle in the foreground image of normal walking and running movements. (a) Normal walking and (b) running movements.

In addition, in order to compare the performance with the most advanced ABD technology, the experiment will iterate the RA with the latest ABD algorithm to obtain the convergence curve and obtain the accuracy of ABD, as shown in Figure 11. It can be seen that the convergence curve of the algorithm proposed in the study is stable, and finally stabilizes with the ABD algorithm at an objective function of around 2.51. The ABD algorithm has a fast convergence speed and a faster decrease in the objective function. Based on the accuracy, the proposed algorithm and ABD algorithm are 0.92 and 0.88, respectively, indicating a higher ABD accuracy of the RA.

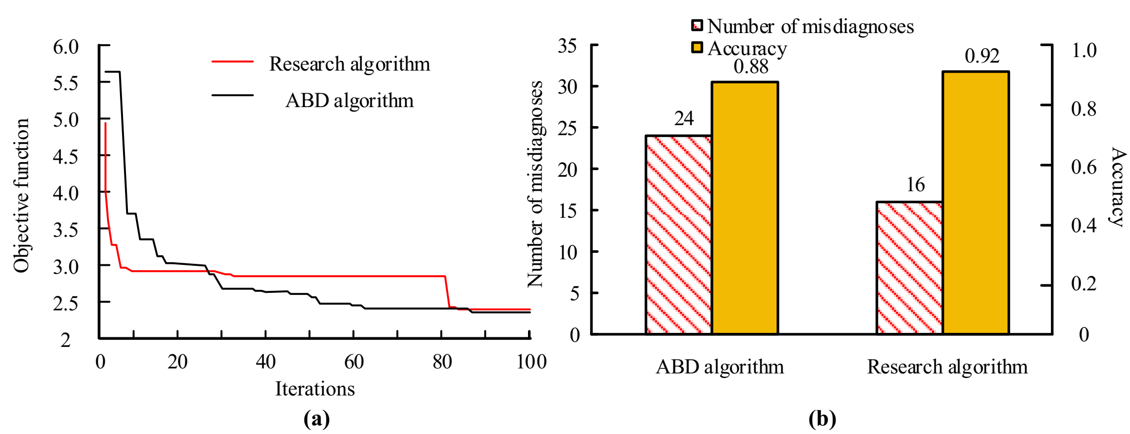

Figure 11: Comparison of convergence speed and accuracy with the latest ABD technology. (a) Iterative convergence curve and (b) tourist ABD accuracy.

5 Discussion

Using a combination of motion foreground effect map features and spatial block detection, the ABD method developed in this research, and based on the background model of optimized GM, a certain level of superiority in recognition efficiency and accuracy has been demonstrated through experiments. It can also offer a reference value for the regulation of AB for tourists in scenic spots. However, there is still insufficient research on the detection of AB in indoor and shadow experiments. Shadows can undergo significant changes with changes in light, and it is necessary to propose methods to eliminate these effects in future research to further improve the effectiveness of object segmentation. The study used background subtraction to construct and optimize a Gaussian model, which solves the problem of being easily affected by background interference in video surveillance detection and recognition. Combining spatiotemporal block detection and motion foreground effect map features, a detection target description method was developed to solve the problem of tourist ABD. In practical applications, researching algorithms can effectively ensure recognition efficiency and accuracy. The method proposed in the study has advantages in scalability or adaptability. In terms of scalability, the study can be applied to various application fields related to video surveillance, such as traffic safety monitoring, public management monitoring, etc. After optimization, the GMM can handle large-scale datasets and is easy to integrate with distributed computing frameworks. By distributing data on multiple nodes for parallel processing, it can significantly improve computational efficiency while maintaining the scalability of the model. In terms of adaptability, the research background model can be dynamically updated and adjusted based on real-time data to adapt to environmental changes. In ABD, the mixed Gaussian model can detect different outliers, and due to its elasticity, it can adapt to different types and quantities of outliers. Further improving the performance factors of anomaly detection methods based on optimized GMMs is an important research direction. The following is an in-depth analysis of these factors and improvement areas: complex GMMs require more computing resources and may face low training efficiency on large-scale datasets. A small dataset may lead to overfitting of the model, while insufficient data diversity may affect the model's ability to identify AB. In addition, improper parameter initialization may lead to slow model convergence or trapping in local optima. Effective selection and extraction of target features can capture key behavioral information and improve the accuracy of anomaly detection. Potential areas for further improvement in research methods include structural optimization, parameter selection optimization, feature selection optimization, computational efficiency, and resource optimization, as well as effective integration with other model algorithms, all of which can further improve algorithm performance.

In addition, the research results can also be widely applied in fields such as public safety, smart homes and security systems, and traffic monitoring and management. By installing surveillance cameras and applying the aforementioned technologies, it is possible to monitor personnel behavior in real-time, detect suspicious or dangerous behavior in a timely manner, and ensure public order and personnel safety. In the home environment, intelligent security systems monitor the behavior of family members through cameras, which is of great significance for ensuring family safety. In the field of transportation, ABD can be used for traffic monitoring and management, real-time monitoring of vehicle driving trajectory and speed, identification of abnormal driving behaviors such as speeding, reversing, and changing lanes without lights, and real-time intervention and punishment through traffic management systems to improve road traffic safety levels.

During the research process, the privacy protection of tourist video information was allowed, and the use of monitoring technology was transparent and fair. When deploying monitoring technology, there were no restrictions or infringements on individual rights and freedoms. Monitoring technology has sufficient security. The processing and deployment of monitoring technology takes into account its impact and responsibility on society.

6 Conclusion

In tourist destinations, the trend is to recognize and provide timely warnings to the staff on the appearance of tourist ABs. However, real-time surveillance video used for manual AB recognition consumes a large amount of public resources and is ineffective. Furthermore, the diversity of application scenarios affects the accuracy of behavior recognition due to the variation in scenic spot backgrounds. To enhance the accuracy of AB recognition, this study presents an ABD approach that utilizes an optimized GM background model. The method merges motion foreground effect map features with spatial block detection. Experiments were conducted to validate the findings. The results indicated that the aspect ratio of the rectangular frame was more balanced and regular during normal walking, whereas during running, the aspect ratio changed more quickly and for a shorter duration. These findings enable the detection of abnormal movements. In scenes b and c, RA showed significantly better performance than the two compared algorithms with AUC and EER values of 88.14, 18.24, 98.12, and 7.55%. However, in scene a, its performance yielded a slightly inferior result with AUC and EER values of 97.31 and 6.29%, respectively, compared to the 95.18 and 12.69% achieved by the HMOFP algorithm. Nonetheless, it was anticipated to be very close to the optimal value and maintained good overall performance. The findings of the experiment show how extremely successful the ABD strategy suggested in the study is in terms of both performance and detection. With the booming development of the tourism industry, the safety and comfortable experience of tourists have become the core elements of tourism area management. The study proposes a background model based on optimized GMM and subsequent ABD methods, which are of great significance in strengthening the safety and management of tourist areas. Through efficient and accurate ABD, strong technical support is provided for the safety management of tourist areas, which not only improves management efficiency and safety, but also enhances tourist satisfaction and loyalty, laying a solid foundation for the sustainable development of tourist areas. Therefore, the tourism area management department should attach great importance to and actively apply this advanced technology to continuously improve the level of safety management and service quality. Although the experimental dataset used by the research institute is a publicly available and authoritative set of ABD videos with relatively simple scenes, actual monitoring videos have the characteristics of variable lighting and complex monitoring content, so more in-depth research is needed. And this study only found relatively common basic ABs. In practical applications, the accuracy of ABD may vary with changes in scenic area's weather, brightness, etc., and may be unstable. Therefore, in subsequent research, the following suggestions were proposed: considering the variable application environment of the algorithm, the possible interference of back and forth motion in the background, and the influence of weather changes, Gaussian mixture background modeling method should be used to construct the background model in the motion detection process. During the detection process, different experiments were conducted for different environments, and several important parameters in the Gaussian model were adjusted to determine the empirical values of important parameters in different environments. A self-adaptive model update rate was studied for the update problem of GMMs in typical algorithms, which significantly improved the modeling speed and reflected the real background image in a more timely manner. This improved the efficiency of the entire model learning and system stability, and eliminated the shadows generated by moving targets to a certain extent. Based on the improved algorithm's motion target detection results, motion target tracking is carried out using the Kalman filter prediction method. Under the premise of effectively detecting motion targets, it can quickly and accurately track targets in simple and more complex environments.

Funding information: The research is supported by Science and Technology Department of Shaanxi Province Study on Protection and Tourism Utilization of Yan'an Red Industrial Heritage under digital technology (2022GY-346); Yan'an University Special project on "Research and Interpretation of the Spirit of the 20th National Congress of the Communist Party of China" (2022YDZX20).

Author contributions: Xiaohua Liu: conceptualization, methodology, software, investigation, formal analysis, data curation, resources, supervision, writing – original draft, writing – review and editing.

Conflict of interest: The author declares that there is no conflict of interest.

Data availability statement: Not applicable.

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