A background modeling algorithm based on improved adaptive Mixture Gaussian

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***Abstract*— For better background modeling in scenes with nonstationary background, a background modeling algorithm based on adaptive parameter adjustment of the Mixture Gaussian is proposed. Mixture Gaussians is applied to learn the distribution of per-pixel in the temporal domain and to control adaptive adjustment of number K of Gaussian components through in increasing, deleting or merging similar Gaussian components adaptively. The new parameters C_k and φ_K are introuced in the adaptive parameter model. According to the actual situation,the adaptive adjustment of ρ can accurate track the real-time changes with the pixel, which improves the robustness and convergence. Experimental results show that the algorithm can rapidly response when the scene changes in the sequence of video with many uncertain factors, and realize adaptive background modeling and accurate target detection.**

***Index Terms*— Gaussian Mixture Model; background modeling; adaptive adjustment $K-\rho$; moving target detection**

I. Introduction

MOVING target detection is the key technology of the video processing in the field of computer vision, the background precise model and accurate segment the target from the video sequence is the basis of target tracking,recognition and behavior analysis. Background subtraction approach [1] [2], optical flow [3] [4] and inter-frame difference method [5] are mostly used in background modeling. However, when the scene is complex, for example: illumination change, water wave and branches shaking, the accuracy and robustness are greatly reduced in background modeling with the background subtraction approach and inter-frame difference method; the computational complexity of the optical flow method is very high, it is difficult to meet the requirements for real-time image processing [6] [7]. Therefore, establishing an adaptive background model under a complex scene becomes critical to determine the effectiveness of the algorithm.

Scholars have proposed many background modeling and target detection method in complex scenes. Stauffer and Grimson [8] [9] constructed background model by Gaussian mixture model.This method can deal with the effects of background mutation.However, after the targets enters into the monitoring area and at a standstill, this method of background modeling prone to "ghosting". And it easily leads to "smear", because the time of background modeling at beginning is relatively long and the learning rate of background updating is relatively slow. Kaew TrakulPon [10] proposed a method to update the model parameters base on traditional GMM algorithm. It used enough statistical information to update the equation at beginning, continue to update the parameters used the basic iterative update equation after the initial background model. This method solved the problem of modeling slow for Gaussian mixture model at beginning, but it does not have application value for learning and updating of the subsequent model. Wren C and Azarbayejani A etc [11] used Gaussian model and class statistical model to detect and track the target. Each pixel has only one Gaussian model in background modeling, it can get smooth background modeling for static scenes, but it is difficult to draw the statistical regularities for complex scenes. Thus,it is difficult with a single Gaussian modeling and, there is no successful application example. Paper [12] proposed a non-parametric background modeling method based on kernel density estimation. This method is not only able to deal with the pixel distribution under complex scenes, but also it able to adapt to the pixels change frequently in a short time. Dar-shyang Lee etc [13] proposed a adaptive learning rate algorithm for Gaussian mixture model, it used adaptive learning rate algorithm to calculate the Gaussian component for every pixel in each frame, The algorithm greatly improved the convergence speed. Paper [14] iteratively computes the maximum posterior probability by EM algorithm and updates the parameters of the Gaussian mixture model. The algorithm has excellent adaptability for complex environments, but the complexity of the algorithm is high and it is difficult to choose suitable model parameters.

We analyzed the traditional Gaussian mixture background modeling which was proposed by Stauffer and Grimson [8] [9], we presented a new algorithm for background modeling. Our new algorithm is based on adaptive parameters adjustment of the Mixture Gaussian,

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since the same pixel at different times or different pixels at the same times must be described by a different number of Gaussian components. In order to accurately describe the background changes and to improve the convergence speed of the background modeling, thi algorithm adaptive adjusts the number K of Gaussian components,through increasing, deleting or merging similar Gaussian components for different situations, In this approach, the model can be effectively expressed for the change of each pixel. As background model is updated with the time change, we introduced the new parameters C_k and φ_k, and adaptively adjusted the value of ρ , so that the model can be accurately updated in real time with the pixel change and the robustness and convergence of the algorithm is improved. The algorithm effectively solves "smear" and "ghosting" problems, and accurately detects foreground objects in real time. In the experimental section, compared with the traditional GMM algorithm in paper [8] [9] and algorithm in paper [14], experiment results show that the new algorithm we proposed is superior to the other two algorithms in terms of background modeling, foreground object detection and algorithm convergence. It proved that our algorithm is feasible and robust.

II. Related Works

The recent history of each pixel, $\{X_1,X_2,\ldots,X_t\}$, is modeled by a mixture of K Gaussian distributions. The probability of observing the current pixel value is

$$P(X_t) = \sum_{i=1}^{n} \omega_{i,t}\eta(X_t|\mu_{i,t}, \sum_{i,t}) \tag{1}$$

Where X_t is the pixel values of one of the pixel at time t, K is the number of Gaussian component, $\omega_{i,t}$ is the weight of the ith Gaussian component, the sum of the weight for each Gaussian component is 1. $\mu_{i,t}$ is the mean and $\sum_{i,t} = (\sigma_{i,t})^2 I$ is the covariance matrix of the ith component at time t. $\sigma_{i,t}$ is the standard deviation and I is the unit matrix. $\eta(X_t|\mu_{i,t}, \sum_{i,t})$ is the normal distribution of the ith component represented by:

$$\eta(X_t|\mu_{i,t}, \sum_{i,t}) = \frac{1}{(2\pi)^{\frac{n}{2}} |\sum_{i,t}|^{\frac{1}{2}}} exp[-\frac{1}{2}(X_t - \mu_{i,t})^T \sum_{i,t}^{-1}(X_t - \mu_{i,t})] \tag{2}$$

Where n is the dimension of support vector X_t.

With the time and scene changes, the Gaussian model of some pixel need to constantly update to establish the appropriate background model. Background modeling process is as follows [15]:

1) According to the descending order of the $\frac{\omega_{i,t}}{\sigma_{i,t}}$ sort the K Gaussian components.

2) Match Detection. The current pixel observed value X_t at time t match with the K Gaussian component, if X_t and $\mu_{i,t}$ meet (3), then the X_t match with the K Gaussian component.

$$|X_t - \mu_{i,t}| \leq or \leq \lambda\sigma_{i,t} \qquad (\lambda\ is\ 2.5 - 3.5) \tag{3}$$

3) Update Parameters. If the current pixel observed value X_t and any one of the K Gaussian component are not matching, then add the $K + 1^{th}$ Gaussian component, and replace the smallest one of $\frac{\omega_{i,t}}{\sigma_{i,t}}$; Conversely, if there are matching Gaussian component, then update the parameters use (4).

$$\begin{cases} w_{i,t+1} = (1-\alpha)\omega_{i,t} + \alpha M_{i,t} \\ \mu_{i,t+1} = (1-\rho)\mu_{i,t} + \rho X_t \\ {\sigma_{i,t+1}}^2 = (1-\rho){\sigma_{i,t}}^2 + \rho(X_t - \mu_{i,t})^T(X_t - \mu_{i,t}) \\ \rho = \alpha\eta(X_t \mid \mu_{i,t}, \sigma_{i,t}) \end{cases} \tag{4}$$

Where α is the Weight learning rate, and ρ is the update rate, the value of $M_{i,t}$ from (5).

$$M_{i,t} = \begin{cases} 1 & \mid X_t - \mu_{i,t} \mid \leq \lambda\sigma_{i,t} \\ 0 & else \end{cases} \tag{5}$$

After the update, each Gaussian component value is normalized by $\omega_{i,t}^1 = \frac{\omega_{i,t}}{\sum_{i=1}^{K}\omega_{i,t}}$

4) Background Modeling. All Gaussian components are sorted by $\frac{\omega_{i,t}}{\sigma_{i,t}}$ descending again, after parameters updated. Then the first B distributions are chosen as the background model, where

$$B = arg\ min(\omega_{i,t}^1 > T) \tag{6}$$

T is a measure of the minimum portion of the data that should be accounted by the background.

III. The Analysis of the Traditional Gaussian Mixture Model

The optimum state of the model updating is that the mean of the model parameters can really reflect the change trend of the background signal by adapting to background change in real time, and the variance can keep the background stable. The key of the model updating is choosing the Gaussian component number K and adjusting the weight learning rate α and update rate ρ.

Parameter Analysis for Mixture of Gaussians Model as follows:

1) Threshold T

If the value of T is small (for example, T =0.1), it will lead to a situation where not all background distribution is covered; if the value of T is large (for example, T = 0.9), it will lead to a situation where the foreground distribution is merging with the background distribution. The T value we used in our program equals 0.79.

2) Gaussian component number K

It generally chooses 3-5 Gaussian components and needs to establish a fixed number of Gaussian model to each pixel that corresponds to RGB three color channels. When a new image arrives, it needs to analyze and update for each pixel corresponding to the Gaussian model. If the number of Gaussian components selected is too big,

then the complexity of calculation will increase and the running speed reduces for pixel with little background change. If the number of Gaussian components selected is too small, the new entrants of moving target will not update fully because of the small number of Gaussian components,which will affect the convergence speed of the model.

3) Update rate ρ

In formula (4), we know that the parameters of each Gaussian component is determined by the variance and mean. The renewal of mean and variance will affect the accuracy and convergence of model update as well as the stability of the model. However, according to the updating method of traditional Gaussian mixture model in formula (4), the value of weights learning rate and update rate are constant, which is likely to cause the instability of model learning. If the value of α and ρ are too large and fast learning rate, it will make the background model update too fast and the slow moving targets will be detected as background. Conversely, it is easy to appear "smear" or "ghosting".

Selecting different number of Gaussian model component and using different learning mechanism about mean and variance will affect the effection of model update, therefore, the background modeling algorithm based on adaptive adjustment $K-\rho$ for Mixture Gaussian is proposed.

IV. THE ALGORITHM BASED ON ADAPTIVE ADJUSTMENT $K-\rho$ FOR MIXTURE GAUSSIAN

A. *The adaptive adjustment Gaussian component number K*

Because of multiple impact factors such as light, fluctuation and so on, the same pixel at different times corresponding to color channel of RGB has change. Therefore, at different times of the same pixel, different Gaussian numbers is described. At the same time different pixel should have different Gaussian component number. Adaptive change of the number of Gaussian components for each pixel is necessary as the time changes, which makes the Gaussian mixture model advanced with fast convergence,low computational complexity and accurate background update.

According to the above analysis, the adaptive adjustment Gaussian component number K is proposed as follows:

1) Add a new Gaussian distribution

If the current pixel observed value X_t and any one of the K Gaussian component are not matching, then the current pixel is regarded as foreground pixel. When the number of Gaussian components does not reach the maximum, the model adds a new Gaussian distribution with the mean of current pixel observed value X_t and initialize parameters use (7), otherwise replace the smallest one of $\frac{\omega_{i,t}}{\sigma_{i,t}}$ with the new one.

$$\begin{cases} \omega_{i,t} < \omega_{init} \\ \mu_{K+1,t} = X_t \\ \sigma_{K+1,t} = \sigma_0 \end{cases} \tag{7}$$

Where $\omega_0$is smaller weight and σ_0 is larger variance.

2) Delete the outdate Gaussian distribution

The weight of Gaussian component is bigger and bigger when it matches the scene for long time. After normalized, if the Gaussian component does not match with the scene, its weight will become smaller and smaller. From (6), those Gaussian components will become the part of foreground. When a Gaussian component of the weights meets (8), the set of pixels that matches the Gaussian component has been for a long time does not appear, so delete this Gaussian component to avoid affecting the scene matching speed and convergence speed.

$$\begin{cases} \omega_{i,t} < \omega_{init} \\ \frac{\omega_{i,t}}{\sigma_{i,t}} < \frac{\omega_{init}}{\sigma_{init}} \end{cases} \tag{8}$$

3) Merge adjacent Gaussian component

After updated, assume G_a and G_b are the adjacent Gaussian components, if they satisfy (9), in order to reduce the computational complexity, then the two Gaussian components are combined into one Gaussian component.

$$\begin{cases} \omega_a < \omega_b \\ \mid \mu_a - \mu_b \mid < r\sigma_a \end{cases} \tag{9}$$

After the merger, the weight, mean and variance satisfy (10) as follow:

$$\begin{cases} \omega_c = \omega_a + \omega_b \\ \mu_c = \frac{\omega_a \mu_a + \omega_b + \mu_b}{\omega_a + \omega_b} \\ \sigma_c = \frac{|\mu_a - \mu_b|}{\lambda} \end{cases} \tag{10}$$

Where r is the pre-merger distribution coefficient and λ is the after merger distribution coefficient, their distribution coefficients were 1.5-2.5 and 1.3-1.5.

B. *Improved parameter updated method based on adaptive adjustment ρ*

On the one hand, generally, the probability of pixels as background is greater than the pixel as foreground in Video Sequence, therefore, the weight of Gaussian component that description background is greater than description foreground in Gaussian mixture model. On the other hand, the background is relatively stable and the color of pixels changes little, however, because moving targets suddenly appear and disappear, such that the foreground of corresponding pixel color values become unpredictable. Therefore, Gaussian component should have a smaller variance describing the background pixel;

conversely, Gaussian component should have a greater variance describing the foreground pixel.

In one word, if the Gaussian component has greater weight and smaller variance, the corresponding pixel is background, conversely, if the Gaussian component has smaller weight and greater variance, the corresponding pixel is foreground.

Update rate ρ reflects the rate of the current video sequence integrate into the background in Gaussian mixture model. From (4), if ρ is smaller, then the mean and variance of the background model update slowly, so the moving targets easily forms "smear". If ρ is greater, then the parameters update too fast, reducing the accuracy and sensitivity for moving targets detection. In conclusion, adaptively choosing ρ become the key of the background modeling when the scene changes. The improved method of the parameters update as follow:

1) Introduce parameter C_k denote the number of effective pixels of the current frame match with model.ρ as follow:

$$\rho = \alpha + \frac{1+\alpha}{C_k} \tag{11}$$

The initial value of C_k is 1, C_k is smaller in the initial phase of background modeling, from (11) ρ is greater, so that the speed of parameters update and background modeling are faster. When the background modeling is stable, C_k is greater and ρ is smaller, which makes the update process slower. In this case, when the moving targets appear or disappear with the scene sudden change, C_k become smaller and rapidly re-establish the background model. When moving targe suddenly stop or it start moving after stopped a period of time, C_k will change from small to large, therefore, the background model real-time change with matching degree. This method solves "smear" and "ghosting".

1) From the definition of Gaussian mixture distribution, if X_t matches with the ith Gaussian component, the match probability as follow:

$$P_i = \begin{cases} \omega_{i,t}\eta(X_t;\mu_{i,t},\sigma_{i,t}) & \mid X_t - \mu_{i,t} \mid \leq \lambda\sigma_{i,t} \\ 0 & else \end{cases} \tag{12}$$

If X_t matches with any one of the Gaussian component, then needs to update parameter of all Gaussian component.We introduce another parameter φ_K as the following:

$$P_i = \begin{cases} 1 & K = arg\ max(P_i) \\ \frac{P_K}{\sum_{i=1}^{K} P_i} & else \end{cases} \tag{13}$$

If component accords with $|X_t - \mu_{i,t}| \leq or \leq \lambda\sigma_{i,t}$, then updating the parameter as follow:

$$\begin{cases} \omega_{i,t+1} = (1-\alpha)\omega_{i,t} + \alpha\varphi_K \\ \mu_{i,t+1} = (1-\rho)\mu_{i,t} + \rho\varphi_K X_t \\ {\sigma_{i,t+1}}^2 = (1-\rho){\sigma_{i,t}}^2 + \rho\varphi_K (X_t - \mu_{i,t})^T (X_t - \mu_{i,t}) \end{cases} \tag{14}$$

V. EXPERIMENTAL RESULTS

To verify the effect of the algorithm proposed, in this section, we use the test videos PetsD1TeC1.AVI, PetsD2TeC1.AVI which were provided by IBM Laboratory, and highway traffic video, campus video which were provided by Computer Vision Research Laboratory of the California University. The experimental environment is based on visual studio 2008, the experimental realization is based on OpenCV. Our algorithm and refs [1], refs [14] were compared.

In order to make the background model as soon as possible for the approximation of the original background image, Weight learning rate α of the first N frames and subsequent frames are defined as follow:

$$\begin{cases} 1/N & N \leq 100, \\ 0.005 & N > 100. \end{cases} \tag{15}$$

1)The background modeling of our algorithm compared with traditional GMM

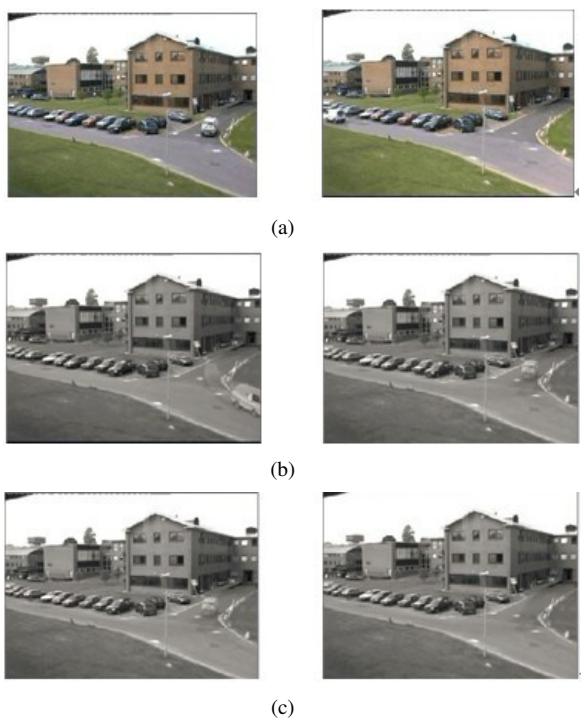

Figure 1. The background modeling of our algorithm compared with traditional GMM. (a). the original image frames of 1968 and 2640 from PetsD1TeC1; (b). the traditional GMM; (c). our algorithm.

The purpose of this experiment is to verify the superiority of our algorithm compared with the traditional GMM. In Fig.1(b), we can see the background modeling of traditional GMM with "smear" at frame 1968. From right figure of Fig.1(b) we can see that the white minibus is about to leave the video at frame 2640, but the background modeling of traditional GMM appears "ghosting". In Fig.1(c), we can see that these two problems were solved by our real-time adjustment K and ρ.

2)Adaptive adjustment K for different video and target detection

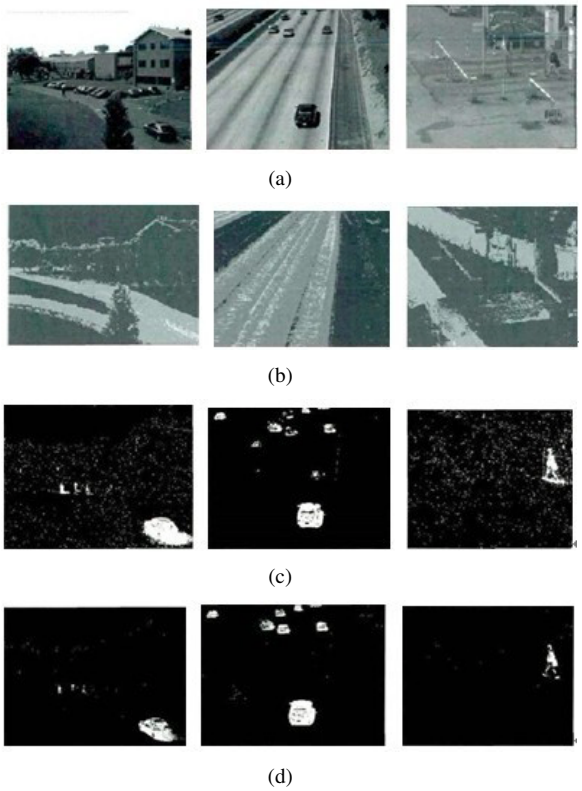

Figure 2. Adaptive adjustment K for different video and target detection;(a). the original image frames from PetsD2TeC1.AVI, highway.avi and campus.avi;(b). the number of Gaussian component;(c). the results of target detection in refs [14];(d). the results of target detection by our algorithm.

Light areas in Fig.2(b) represented target moving frequently and pixel values change is larger, so relatively large number of Gaussian components were used for the background modeling. On the contrary, the deep color in Fig.2(b) represented moving target rarely appears and pixels values change little, so relatively small number of Gaussian components were used for the background modeling.

Comparing Fig.2(c) and Fig.2(d), we can see that the accuracy of target detection is better by our method, however, the algorithm in refs [14] appears interference from the large area of noise, the target detection results contain a lot of noise region, so that it likely to cause the target detect error.

3)Background modeling and target detection

In Fig.3(a) the blue car parked in the corner at frame 690, in this paper the first image is the frame 768.

Comparing Fig.3(b) and Fig.3(c), the blue car gradually became a part of background when background modeling by our method, therefore, the blue car is no longer as foreground object when detecting the target. However, the traditional GMM is difficult regarding the blue car as part of background, so it was detected as foreground object in Fig.3(e). At frame 1068, we can see that our method has been completely considered the blue car as part of the background, but from Fig.3(e), the traditional GMM still detected it as foreground. The white minibus began

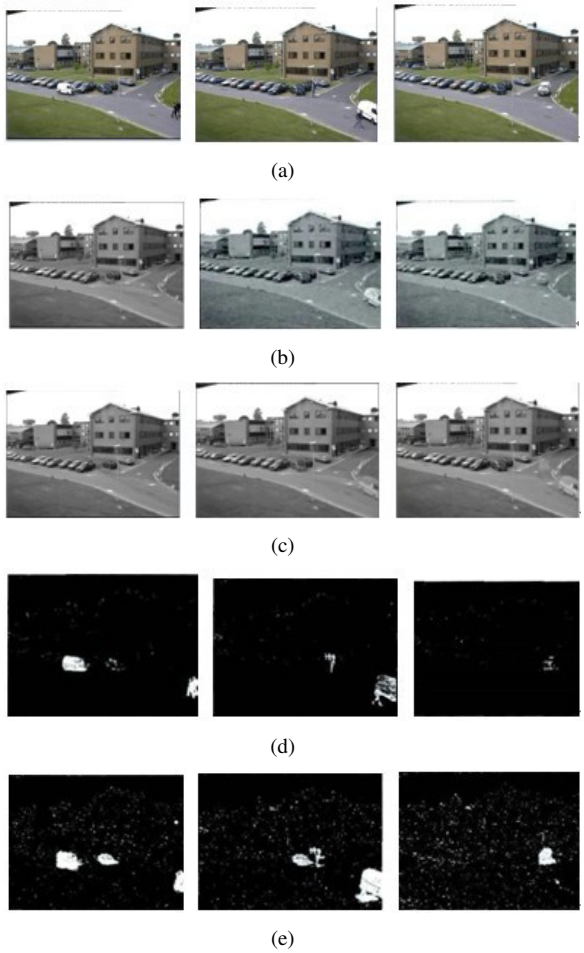

Figure 3. Background modeling and target detection for different frames in the same video. (a). the original image frames from PetsD1TeC1, from left to right is frame 768, 1068 and 1968; (b). background modeling by our method; (c). background modeling by the traditional GMM; (d). target detect by our method; (e). target detect by the traditional GMM.

to move in the lower right corner at frame 1635, to the frame 1968 the minibus stopped at the position shown in Fig.3(a). We can see that the background modeling of traditional GMM appears "smear" at frame 1968 in Fig.3(c). In Fig.3(b), our method solved the problem. In Fig.3(d) and Fig.3(e), we can see the performance of background modeling and target detection greatly improved.

VI. Conclusions

We presented a new algorithm for background modeling, which based on adaptive adjustment $K-\rho$ for Mixture Gaussian. Our method is effective to improve the convergence rate and to solve the problem of the model updating not enough. Firstly, mixture of Gaussians is utilized to learn the distribution of per-pixel in the temporal domain, and constructed the approach of adaptive adjustment the numbers K of GMM component. Secondly,our method introduces new parameters C_k and φ_K into the update formula of parameter model. According to the actual situation, adaptive adjustment of the value of ρ makes the background model updated which can track real-time changes with the pixel accurately. This approach

improves the robustness and convergence. Experimental results demonstrate that the new algorithm is effective to solve the ”smear” and ”ghosting” in nonstationary scenes and the results show great adaptability and robustness for the background modeling and target detection.

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