Adaptively Adjusted Gaussian Mixture Models for Surveillance Applications

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Abstract. Segmentation of moving objects is the basic step for surveillance system. The Gaussian Mixture Model is one of the best models to cope with repetitive motions in a dynamic and complex environment. In this paper, an Adaptively Adjustment Mechanism was proposed by fully utilizing Gaussian distributions with least number so as to save the amount of computation. In addition to that, by applying proposed Gaussian Mixture Model scheme to edge segmented image and combining with data fusion method, the proposed algorithm was able to resist illumination change in scene and remove shadows of motion. Experiments proved the excellent performance.

1 Introduction

Background subtraction is a conventional and effective solution to segment the moving objects from the stationary background But in an actual scene, the complex background such as snowy or windy conditions, make the conventional algorithm unfit for the real surveillance systems. Stauffer and Grimson [1][2] proposed to model each pixel by a mixture of Gaussians. Saeid et al. [3] proposed an improved method based on GMM, but it was not able to cope with illumination change and shadow problem. Huwer et al. [4] proposed a method of combining a temporal difference method with an adaptive background model subtraction scheme to deal with lighting changes. J. Zhan et al. [5] analyzed the foreground by GMM and operated the classification based on SVM method, high accuracy were achieved, but with a high computation cost. To save huge computation load for surveillance system, the Adaptive Adjustment Mechanism was proposed. Moreover, laplacian edge segmented image was utilized in our method as the input of the modified GMM. To improve the quality of segmentation, data fusion mechanism is put forward to make up the lost information. The remaining parts for this paper are arranged as follows. Section 2 introduces the conventional GMM procedure and describes Adaptively Adjustment Mechanism. Section 3 specifies analysis of applying edge-based image segmentation and data fusion scheme. Section 4 and Section 5 present the experimental results and conclusion respectively.

S. Boll et al. (Eds.): MMM 2010, LNCS 5916, pp. 689–694, 2010.

2 Adaptive Adjustment Mechanism for Gaussian Models

2.1 Gaussian Mixture Model

According to the original GMM, the pixel process is considered a time series of vectors for color images. The algorithm models the recent history of each pixel as a mixture of K Gaussian distributions. A match is found if the pixel value is within 2.5 standard deviation of a distribution. If current pixel value matches none of the distributions, the least probable distribution is updated with the current pixel values, a high variance and low prior weight. After the prior weights of the K distributions are updated the weights are renormalised. The changing rate in the model is defined by $1/\alpha$. α stands for learning rate. And parameters for matching distribution are updated. The Gaussians are ordered based on the ratio of ω/σ. This increases as the Gaussian's weight increases and its variance decreases. The first B distributions accounting for a proportion of the observed data are defined as background.

2.2 Adaptive Adjustment Mechanism

Even though K (3 to 5) Gaussian distributions are capable of modeling a multimodal background, the huge number of total Gaussian distributions induced a great computational load for surveillance system.

In fact not all the pixels of the background objects moved repetitively or changes diversely all the time. For the areas where less repetitive motion occurs, such as the ground, houses and parking lot in the scene of Fig. 1(a), it is easy to find that the first and second highest weighted Gaussians (Fig. 1(b) and (c)) are

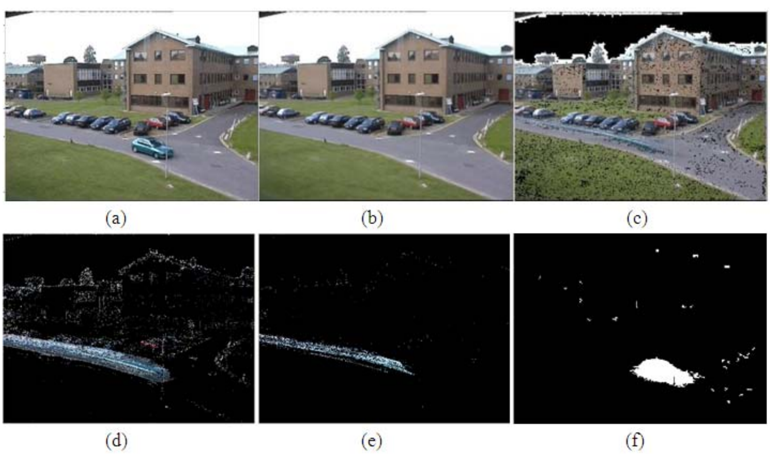

Fig. 1. (a) The 363th frame from PetsD2TeC2 [6]; (b) M_1st_WG(The Mean of 1st Weighted Gaussians); (c) M_2nd_WG; (d) M_3rd_WG; (e) M_4th_WG; (f) Foreground mask by GMM

adequate to model the mult-possibilities of background variability. So adaptive Adjustment Mechanism was proposed to drop unnecessary Gaussians component which contributed less to the multi-possibilities for modeling background, then adaptive number of distribution could be adopted for different pixels according to their corresponding value changing history. The update of weight, mean and variance for our proposal is based on online EM algorithm [7].

E-step: As the online EM algorithm does, it begins from estimating of the Gaussian Mixture Model by expected sufficient statistics, which is called E-step. Due to the unpredictable possibilities for the complexity of background pixel, and the first L frames is very important for Gaussian models to dominant background component and achieve stable adaptations. And then keep the number of Gaussians models, K, fixed during E-step. Experiments also show these could provide a good estimation which helps to improve the accuracy for M-step process. For initialization part, we define a parameter $N_{i,j}$ to record number of Gaussian models for the pixel at the position *(i,j)* in each frame, also a parameter called *sum_match* to record the sum of matches for a particular Gaussian distribution.

M-step: The L-recent window update equations give priority over recent data therefore the tracker can adapt to changes in environment. When a new pixel value comes, check it against first $N_{i,j}$ Gaussian distributions in turn. If the i_{th} distribution G_i matches, update parameters as M-step in EM does. After that, we compare the value of ω_i/σ_i with value of $\omega_{i-1}/\sigma_{i-1}$. If $\omega_i/\sigma_i > \omega_{i-1}/\sigma_{i-1}$, exchange the order of G_i and G_{i-1} and operate $i = i - 1$, repeat it until $i = 1$ or $\omega_i/\sigma_i \leq \omega_{i-1}/\sigma_{i-1}$. Or else no match found, operate as follows:

$$N_{i,j}^{k} = N_{i,j}^{k-1} + 1, \;\; if \;\; N_{i,j} < K; \;\; N_{i,j}^{k} = K, \;\; if \;\; N_{i,j} = K \tag{1}$$

then replace the mean value of the N_i, j_{th} distribution with current pixel. After that the Gaussians are eliminated from least updated ones according to two parameters: value of weight, which represent the time proportions that those colors stay in the scene and *sum_match*, which takes for the percentage of importance in K guassians to dominant background component from history.

$$\omega_k = \frac{\omega_k}{\sum_{i=1}^{N_{i,j}} \omega_i}, \quad k = 1, 2, ...N_{i,j} \tag{2}$$

where $N_{i,j}$ is the number of left Gaussians.

As this adaptive Adjustment Mechanism processes with GMM, the stable value pixels did not need K Gaussians modeling for adaptation. The total number of Gaussians of PetsD2TeC2 with a resolution of 384x288, 2821 frames was experimented shown as Fig. 2. When comes to M-step, obvious decrease occurred. Especially when larger the K is, more unnecessary Gaussians were eliminated.

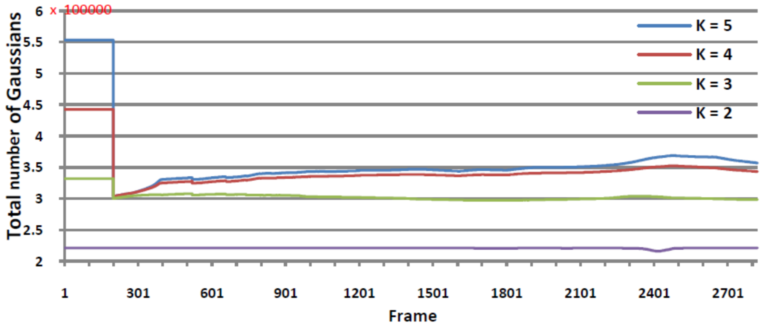

Fig. 2. The total number of Gaussians for each frame based on different value of K

3 Laplacian Edge Detection and Data Fusion

Even though GMM is capable of dealing with complex environment especially unpredictable repetitive motion, two major problems influence the detection accuracy when applying GMM to surveillance system: illumination changes and shadow of moving objects.

In our proposal, the well-known Laplacian edge detection method was utilized since it runs very fast and achieves good results. And then the improved GMM method mentioned above was applied to the mask generated by laplacian edge detection. Because laplacian operator could enhance the effect of edges of object, so the influence from illumination and shadow area were weakened intensively (refer to Fig. 3(c)). Considering this point of advantage, the edge segmented grey level information from video stream was proposed to act as input of improve GMM to avoid illumination influence and shadows. Meantimely, even though edge of motion was clear and shadow of people was removed, inside hole of motion appeared in the detection mask. To solve this problem, we proposed data fusion scheme.

We named the mask by applying GMM on RGB color space as *Mask_RGB*, and the mask by applying GMM on laplacian edge segmented image as *Mask_Edge*. *Mask_RGB* contains all the information of moving objects except repetitive motion, and also misclassified foreground. In the other hand, *Mask_Edge* excludes the misclassified foreground pixels, but it lost information inside of motion. In the proposal, *Mask_Edge* takes an important role as a criterion to confirm the foreground pixels in *Mask_Edge* whether are correctly classified. For a foreground pixel in $Mask\_RGB(i,j)$, neighboring foreground pixels in a 6x6 region centered as $Mask\_Edge(i,j)$ is checked, we define a threshold, which equals to 6 for indoor and 3 for outdoor. And compared with this number we can determine whether $P(i,j)$ should belong to foreground or background.

4 Experimental Results

Our experimental results is based on the 4 outdoor sequences and 3 indoor sequences from [6]. Proposed background modeling method is evaluated by the metric proposed by Black et al. in [8]. Through this method for data fusion, some noise can also be removed. As the Fig. 3 (d) below shows, it is clear that shadow was removed from motion, and illumination changes did not influence

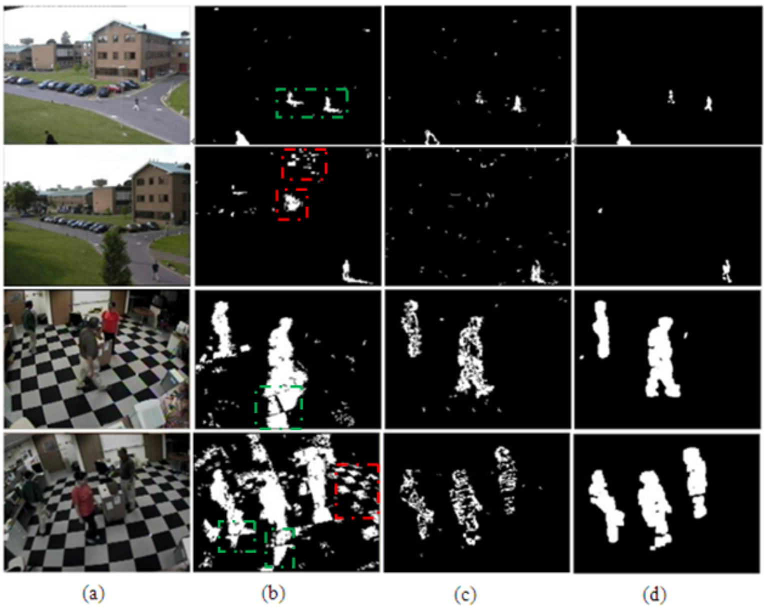

Fig. 3. Comparison of foreground: (a) original frames; (b) Foreground mask of GMM_RGB (shadow noted by green contour, and influence caused by illumination changes by red). (c) Foreground mask of GMM_RGB. (d) Foreground mask by proposed algorithm.

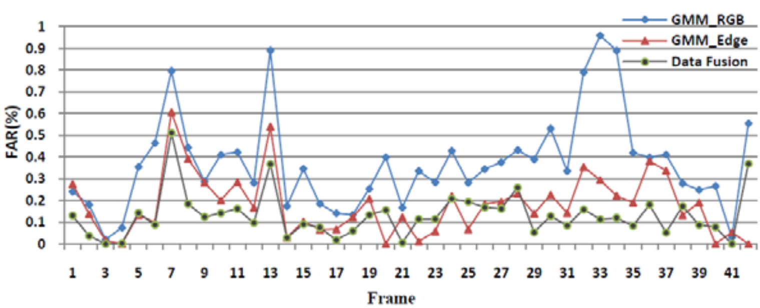

Fig. 4. False alarm rate for every 60th frame of PetsD2TeC2 sequence

the segmentation results. Compared with Fig. 3(c), inside information of moving objects was filled up. For indoor sequence, foreground is a little shattered, if adding the postprocessing filter in final step, results would be better. The FAR (False Alarm Rate) is shown as Fig. 4.

5 Conclusion

This paper presented an effective and efficient algorithm based on Gaussian Mixture model for surveillance system. An adaptive Adjustment Mechanism is proposed to reduce the number of Gaussian distributions. Additionally, aiming at excluding the influence by illumination and shadow problem, we proposed to apply our improved GMM on the laplacian edge segmented image, and a data fusion mechanism is put forward to solve the problem of losing inside motion information. The results of segmentation by proposal consequently proved its effectiveness and efficiency. Experiments show the detection rate and false alarm rate between different methods, which validated the improvement on detection accuracy and segmentation quality.

Acknowledgments. This work was supported by fund from MEXT via Kitakyushu innovative cluster projects and CREST, JST.

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