An Adaptive Background Modelling Method For Foreground Segmentation

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Abstract

Background modelling has played an important role in detecting the foreground for video analysis. In this paper, we presented a novel background modelling method for foreground segmentation. The innovations of the proposed method lie in the joint usage of the pixel-based adaptive segmentation method and the background updating strategy, which is performed in both pixel and object levels. Current pixel-based adaptive segmentation method only updates the background at the pixel level and does not take into account the physical changes of the object, which may result in a series of problems in foreground detection, e.g., a static or low-speed object is updated too fast or merely a partial foreground region is properly detected. To avoid these deficiencies, we used a counter to place the foreground pixels into two categories (illumination and object). The proposed method extracted a correct foreground object by controlling the updating time of the pixels belonging to an object or an illumination region respectively.

Keywords: The Background modelling method, pixel-based adaptive segmentation, and adaptive background updating method.

1. Introduction

Background subtraction is the first and one of the most vital parts of autonomous vision system used in visual surveillance, motion detection applications and human-computer interaction systems. Basically, background subtraction procedure means the comparison of current frame with reference background model. If a pixel in the current frame is matched to the background model, it is classified as background. Otherwise, it is a foreground pixel. After this process, the mask showing only foreground objects are acquired for object analysis process.

Earlier, the background subtraction process was performed by the so primitive methods that were not able to cover the whole foreground pixels. However, as the challenges in background subtraction such as illumination changes, camera noise, non-static backgrounds, shadows and weather conditions (rain, snow) arise, these methods remain inadequate to handle these kinds of difficulties. Therefore, more complicated and effective algorithms probabilistic methods, Mixture of Gaussians and Codebook Background Modeling are designed for creating for a more robust and adaptive background model.

The performance evaluations of the background subtractions are indispensable to calculate their accuracy and to find the ideal parameters for optimal results. There are two main concepts on performance evaluation [3]. The first concept is Ground-truth (GT) which is based on manually annotations of video foreground objects [4] [5]. In this methodology, all foreground objects are defined manually frame by frame. The other concept is not-based on Ground-truth (NGT) whose annotations are created automatically when the algorithms are operating. However, due to the difficulty on defining a criterion for good subtraction performance, it has been rarely used by video- surveillance community [6][7].

2. Literature Review

Background Subtraction algorithms are evaluated in four different groups. These groups named as Pixel difference based methods, Probability based methods, and Codebook based methods and other methods. Some methods in these groups are easy to implement while others are very complicated methods. Furthermore, a number of algorithms in these groups have a capability to handle multimodal background whereas other approaches are not able to deal with multimodal background. Numerous algorithms from these groups are able to cope with camera noise, illumination changes, but others cannot handle such problems. After the algorithms, a few post- processing methods such as morphological operations and connected component labeling to improve the performance of the subtraction algorithms are mentioned.

3. The proposed pixel-based adaptive segmentation method

Vibe initializes the background model using only the first frame and the threshold for foreground segmentation is fixed. This limits the adaptability of ViBe. PBAS was proposed to improve ViBe. PBAS incorporates the ideas of several foreground detection methods and control system theory and is a non-parametric background modelling method. Following the basic idea of ViBe, PBAS also uses the history of N frames to construct a background model. For the background pixels and its neighbouring ones, they will be updated with a random scheme. Unlike ViBe, PBAS initializes the background model using the first N frames and classifies the foreground pixel using the dynamic threshold which is estimated for each pixel. Moreover, the adjustable learning rate lying in PBAS can control the speed of background updating. The diagram of PBAS is presented in Fig. 1.

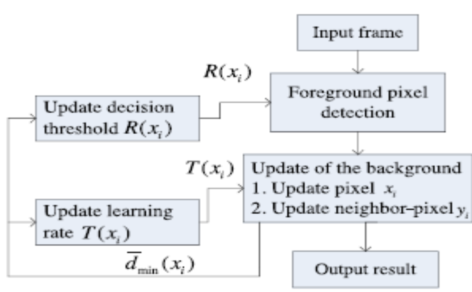

Figure 3.1 Diagram of the PBAS method.

From Fig. 1, it can be seen that the algorithm has two important parameters: the segmentation decision threshold $R(xi)$ and background learning rate $T(xi)$. We define the background model $B(xi)$ at pixel xi as $B(xi) = \{B1(xi), . . . ,Bk(xi), . . . , BN(xi)\}$ which presents an array of N observed values at pixel xi. Pixel xi is classified as the foreground pixel according to

$$F(x_i) = \begin{cases} 1 & \#\{\text{dist}(I(x_i), B_k(x_i)) < R(x_i)\} < \#_{\min} \\ 0 & \text{else} \end{cases} \quad (1)$$

Where $F(xi) = 1$ means that pixel xi is a foreground pixel, and $F(xi) = 0$ means that xi is a background pixel. $I(xi)$is the pixel value of pixel xi. The distance threshold $R(xi)$ can be dynamically changed at each pixel over time.$\#\{\text{dist}(I(xi), B(xi)) < R(xi)\}$ is defined as the numbers of the pixels located at xi when the distance between pixel value $I(xi)$ and background value $Bk(xi)$ is less than $R(xi)$, and threshold #min is predefined and fixed. Since the dynamic changes of the background at each frame, $R(xi)$ needs to automatically adjust as follows:

$$R(x_i) = \begin{cases} R(x_i) \cdot (1 - R_{\text{inc/dec}}), & \text{if } R(x_i) > \bar{d}_{\min}(x_i) \cdot R_{\text{scale}} \\ R(x_i) \cdot (1 + R_{\text{inc/dec}}), & \text{else} \end{cases} \quad (2)$$

where Rinc/dec and Rscale are fixed parameters. $\bar{d}\min(xi)$ is defined as $\bar{d}\min(xi) = 1/N \sum_k \min(I(xi), Bk(xi))$, and is anaverage of N minimal distances between pixel value $I(xi)$ and background pixel value $Bk(xi)$ at pixel xi . So the change of $R(xi)$ is determined by $\bar{d}\min(xi)$. The other parameter is the background learning rate $T(xi)$ which controls the speed of the background absorption. A large $T(xi)$ means that a foreground object will be merged into the background quickly. The method defines the updating rule of the learning rate $T(xi)$ as follows:

$$T(x_i) = \begin{cases} T(x_i) + \frac{T_{\text{inc}}}{d_{\min}(x_i)}, & \text{if } F(x_i) = 1 \\ T(x_i) - \frac{T_{\text{dec}}}{d_{\min}(x_i)}, & \text{if } F(x_i) = 0 \end{cases} \quad (3)$$

where$T$inc and Tdec are fixed parameters. They are independently set to increase or decrease $T(xi)$. Furthermore, the method defines an upper bound Tupper and lower bound Tlower to prevent $T(xi)$ from exceeding the normal range. When $T(xi)$ is larger than Tupper or smaller than Tlower, the PBAS makes $T(xi) = T$upper or $T(xi) = T$lower respectively. In fact, the method does not directly employ the learning rate $T(xi)$, but randomly updates the background pixels with probability $p = 1/T(xi)$. The lower the $T(xi)$ is, the higher the p will be, which also means that the pixel will be updated with higher probability.

4. Description of the proposed method

We updated the background models by introducing a selective updating strategy. The background model can be updated at both pixel level and object level. Our updating strategy enables the background to adapt to the changes of object and illumination. The proposed method can rapidly remove the influence of lighting changes and retain the shape of the foreground object. Aiming at distinguishing the change of illumination from the change of the object, we constructed a counter (similar to [17]), COM, which counts the times that each pixel is continuously identified as a foreground pixel. For pixel m in the t-th frame, we increased the value of COM$t(m)$ by 1 when this pixel is classified as the foreground pixel. Once the pixel is classified as a background pixel, COM$t(m)$ is set to zero. The procedure is presented as:

$$\begin{cases} \text{COM}_t(m) = \text{COM}_{t-1}(m) + 1 & \text{if } F_t(m) = 1 \\ \text{COM}_t(m) = 0 & \text{otherwise.} \end{cases} \quad (4)$$

In other words, the value of COM$t(m)$ shows the number of frames in which pixel m is continuously marked as the foreground pixel. It implies that pixel m belongs to an object if COM$t(m)$ is very large. The maximum of COM(m) at pixel m is always small when this pixel is in a region with a strong change of lighting, because changes of illumination often cause sudden appearance and disappearance of lighting and shadow. However, for a pixel of an object, particularly a motionless or low-speed motion object, the value of COM(*m*) is always sufficiently large. By using an appropriate threshold, we can distinguish the change of a lighting pixel from the change of an object pixel. The designed method starts to update the neighbouring pixels of pixel *m*, when the value of COM(*m*)is larger than threshold *Tb*. The proposed updating process is similar to the neighboring pixels updating process of PBAS ,and it used randomly selected neighboring pixels of pixel *m*to replace the randomly selected background sample pixels of corresponding location. The purpose of this method is to weaken the diffusion effect when the background updates the foreground objects for obtaining the almost complete shape of a foreground object.

For the region of illumination changes, however, the maximum of COM(*m*) does not always exceed threshold *Tb*. So the background updating diffusion effect can rapidly remove the region of lighting changes. From our experience, the variance of threshold *Tb* cannot obviously affect the result. So we can fix it as an appropriate value. This updating model works well in most cases. However, when the initial frames contain a foreground object, the model cannot adaptively update an incorrect background caused by the initial frames. Fig. 3 shows such an instance. In the video “baseline highway” of the Change Detection Challenge dataset, a car is emerging in the scene in the beginning of the video. Fig. 3(a) shows a beginning frame which is used to initialize the background model. Fig. 3(b) and (c) present a source image and detection result. It can be seen that the “first car” is still in the result image. This is because the initial background object region is again detected as a foreground object, while in fact, no true object appears in this region at that time. So it can be regarded as a “static object” in the scene. Whether or not an object passes that background object region, the “static object” will be kept in the scene. Even through the values of counter COM of some pixels from that background object region exceed threshold *Tb*, the diffusion effect of the background updating is not obvious for those pixels. The object background region cannot be updated by a new background. This leads to incorrect detection results for the whole sequence.

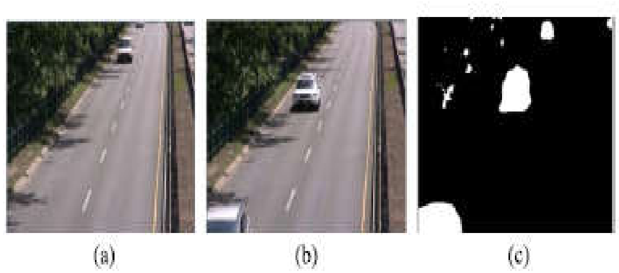

Fig4.1 Example of incorrect foreground object caused by initialization.

(a) Beginning frame of the video. (b) Source frame. (c) Detection result.

In order to overcome the above disadvantage, we proposed another background updating strategy.

ALGORITHM:

The proposed method is summarized in Algorithm 1.

Algorithm 1: An Adaptive Background Updating Algorithm

Input: A frame.

Output: A binary image.

Initialization: First *N* frames are used to construct the background model. Counter COM is set to 0

Procedure:

1. Pixel *m* is classified as a foreground pixel or background pixel;

2. If pixel *m* is classified as a background pixel

a) replace randomly selected background sample pixel *Bi*(*m*) with pixel *m*, *i* is a random number;

b) if COM *t*(*m*)>*Tb*, randomly select the neighbouring pixel *p* of pixel *m* and update this pixel into a randomly selected background sample pixel *Bi*(*p*) of pixel *p*, *i* is a random number;

c) counter COM *t*(*m*) is set to 0;

3. If pixel *m* is classified as a foreground pixel

a) 1 is added to counter COM *t*(*m*);

b) if COM *t*(*m*) >*Tf*, replace randomly selected background sample pixel *Bi*(*m*) with pixel *m*, *i* is a random number.

5. Implementation & result

An Adaptive Background Updating Algorithm is used to get an binary output with the help of matlab. Firstly we provided an input frame to the algorithm with serious of steps as shown in the figure1

Fig5.1 video frame

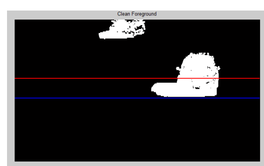

Fig5.2 clean foreground

We proposed another background updating strategy. We used a random strategy to regard pixel *m* whose COM *t*(*m*) exceeds threshold *Tf* as a background pixel. The updating process replaces pixel *m* with a randomly selected background sample pixel, whose strategy is similar to. This means that if a pixel is marked as a foreground pixel for a long time, it may become a new background pixel. This method can remove the incorrect background region which is caused by an initial foreground object, because the “static object” caused by an incorrect background region can be easily updated into the background. Then the updated objects will count by the counter and gives the total no of detected objects count as shown in the figure 5.

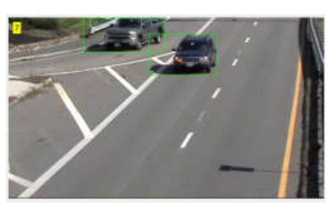

Fig5.3 detected objects.

5. Conclusion/Future Work

In this paper, we proposed a robust and effective background modeling method. The proposed method uses the advantages of the pixel-based adaptive segmentation method. PBAS only updates the background at the pixel-level. So it causes motionless or low-speed motion objects to be absorbed by the background quickly, or partial regions of the foreground objects are neglected. The proposed method adopts a updating strategy that can update the background at the pixel level and object-level. We constructed a counter to record the times in which a pixel is continuously classified as a foreground pixel for all image pixels. We can control the updating time by using the value of the counter. This updating mechanism can work well in most scenarios. The experimental results show that our proposed method can achieve better results than other methods. Because of the lower computation time, our method can adapt to many real-time applications. We also attempt to design a procedure to count number of objects in the scene.

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