International Journal of Emerging Engineering Research and Technology
Volume 3, Issue 4, April 2015, PP 86-92
ISSN 2349-4395 (Print) & ISSN 2349-4409 (Online)

BMM Based Cauchy Distribution (BMMC) Method for Motion Detection

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ABSTRACT

Video surveillance systems are playing a vital role in security, military, business, environmental activities. Due to the social problems and for loss prevention video surveillance systems are of critical importance. Motion detection plays a real time role in video surveillance systems because of the usage of static cameras. This paper proposes motion detection with a new background matching model and a Cauchy distribution model. The background model is a self-adaptive model which selects the background pixel at each frame in regard to background model generation. After the generation of background model, the binary motion mask is generated with Cauchy distribution model. The object motion mask computation is done using absolute difference estimation. This method also determines detection quality and accuracy by using qualitative and quantitative measurements. The experimental results of proposed method demonstrate the effectiveness with low computational cost.

Keywords: Background matching model, Cauchy distribution model, video surveillance, motion detection.

INTRODUCTION

Video surveillance systems have become widely spread during recent times to ensure safety, security in business, military and many private as well as private sectors. In general these video surveillance systems are developed with motion detection methods. Moreover, motion detection has been used in many domestic and commercial applications. According to the related survey, the motion detection can be categorized into three classes i.e., temporal difference, optical flow, and background subtraction .temporal difference methods readily adapt to sudden changes in the environment, but the resulting shapes of the moving objects are often incomplete. Optical flow method generally show the projected motion on the image plane with good approximation based on the characteristics of flow vectors. But, flow vectors of moving objects only indicate streams of moving objects, thus detecting a sparse form of object regions. Moreover, the computational complexity of optical flow method is too high. Out of these three, the background subtractions receive more attention due to moderate time complexity and accurate detection of moving entities. This motion detection can be done using Cauchy distribution method with the proposed high quality background model. Our proposed method can be organized here.

- A self-adaptive background matching frame work is proposed to select suitable background candidates of background model generation.
- The conditional Cauchy distribution model is applied to extract moving objects of the video sequence.

Based on the qualitative and quantitative results, experiments will verify that the proposed method is more efficient than other methods in terms of motion detection

BACKGROUND

Here we compare background model with three existing methods. Those are MTD (Multi temporal difference) method, a Gaussian mixture model (GMM) method, and a multiple sum difference

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estimation (MSDE) method. MTD method holds previous frames instead of background generation, the computational cost is low, and holes are reduced inside moving entities. However, each held frame may include moving objects to drag ghost artifacts in the detection results.

Compared with the single background model, GMM and MSDE methods use several temporal terms to generate multiple reference images, which are applied to calculate a mixture background model. Unfortunately, these methods cannot detect moving objects well since the multiple and clutter motion may drag ghost artifacts to the background model. To compensate for the limitations of these methods, a method must be developed to create a background model without ghost artifacts in terms of motion detection. To achieve this objective a background matching frame work should be designed to select the possible background pixel at each frame by using the video stream.

One more subtraction method which we are going to compare is background subtraction method. This method employs the rule of subtraction of the current image and the background image to detect moving targets. The idea involving is the first frame image is stored as the background image . Then the current frame image with the pre-stored image then results in background subtraction, and if pixel image is greater than certain threshold, then it determines pixel to pixel on moving targets or as background pixel. The choice of threshold of background subtraction is very important to achieve success. If the threshold value is too small, will leads to lot of false points on the background .If the threshold value is too large, will reduce the scope of changes in the movement. So the choice of dynamic threshold would be selected.

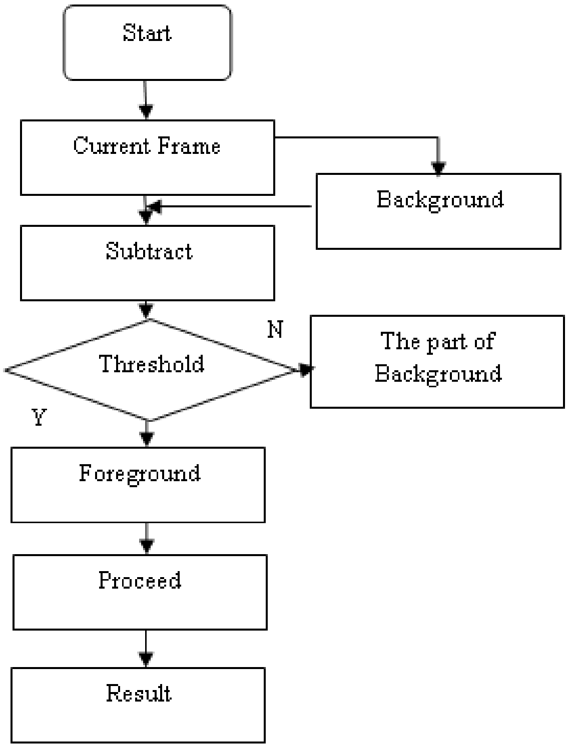

Fig1. *Background Subtraction Method*

PROPOSED APPROACH

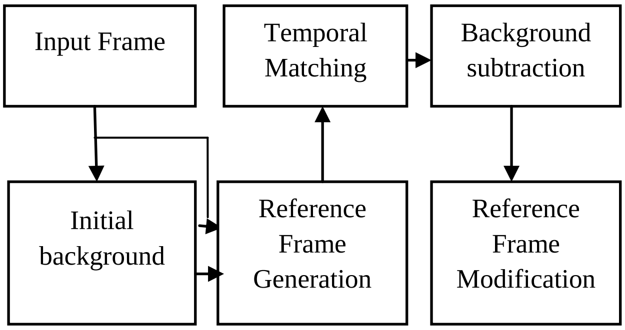

Fig2. *Flow chart of the proposed Approach*

Here, we propose a motion detection method with a new background model. Fig.1 shows the flow chart of proposed method. For the quick determination of the suitable back-ground region each pixel is checked by the temporal match method at each frame of BMM. Subtracting the generated background model from each frame so that we will be obtaining absolute difference values. Finally, we develop a conditional Cauchy distribution model to generate an accurate motion mask for the accurate detection of moving objects at each frame.

There are two major steps involved in implementation of our proposed technique

A. Background model generation

1). Initial background model. 2). BMM.

B. Motion mask generation

1).Absolute differential estimation. 2) Cauchy distribution model.

Background Model Generation

Initial background model: For appropriate background model generation, initialization is necessary. The average obtained at the input video sequence well suffices as the initial approximation of background. Therefore, the average of the prior K frames must be first calculated for initial background model generation.

$$B_t(x,y) = \frac{1}{k}\sum_{t=0}^{k-1} I_t\,(x,y) \tag{1}$$

Where $I_t(x,y)$ represents the incoming video frame, $B_t(x,y)$ represents the background model, t represents the frame number, and K is experimentally set at 30 to calculate the initial background model.

- BMM: After generating the initial background model, the proposed background matching mechanism (BMM) can be used to modify the background image at each frame. The flow chart of the proposed BMM method is as shown in fig2. The stages in the flowchart can be explained as below.
- Reference frame generation: To obtain the background image without moving object the reference frame should be calculated at each frame. For each pixel, the reference frame can be calculated as shown below.

$$M_t(x,y) = M_{t-1}(x,y) + sgn(I_t(x,y) - M_{t-1}(x,y)) \tag{2}$$

Where $M_t(x,y)$ represents each pixel value of current reference frame, $M_{t-1}(x,y)$represents each pixel value of the past reference frame. Note that M_t initialized by the initial background model with a frame index K-1 at the frame.

$I_t(x,y)$ represents each pixel value of the current input frame.

- Temporal match: Based on reference frame generation we can easily define the current set of background candidates to obtain the background model. For each pixel,if $M_t(x,y)= I_t(x,y)$ then $I_t(x,y)$ is regarded as a background pixel. Otherwise, the input pixel is eliminated from the background candidates.
- Background modification: after determining the background candidates at each frame, the current background model can be calculated as shown below.

$$B_t(x,y) = B_{t-1}(x,y)+sgn(M_t(x,y)- B_{t-1}(x,y)) \tag{3}$$

Where $B_t(x,y)$ represents the current background model and $B_{t-1}(x,y)$ represents the previous background model and $M_t(x,y)$ represents a current set of background candidates, which is equivalent to $I_t(x,y)$.

- Reference frame modification: Based on the temporal match and background modification each modified pixel of the background model can be further used to update the reference frame $M_t(x,y)$. since each pixel of the input frame can be strictly matched in terms of determining the background candidates, the background model can be updated without the noise pixel of the input image at each frame. Moreover, the reference frame is also updated by the modified background pixel. Hence, the self-adaptive background model can be generated by this proposed BMM.

Motion Mask Generation

- Absolute difference estimation: Based on the proposed background model module, the absolute differencing image $\Delta_t(x,y)$ can be generated by calculating the modulus of the difference between the background model and the incoming video at each frame. The equation is as shown below.

$$\Delta_t(x,y) = \left| B_t(x,y) - I_t(x,y) \right| \quad (4)$$

- Cauchy distribution model:

The accurate detection of the pixels of the moving objects in the absolute differencing image at each frame can be done via Cauchy distribution method. The expression is as shown below:

$$f(\Delta_t(x,y);\, a,b) = \frac{1}{\pi}\left[\frac{b}{(\Delta_t(x,y)-a)^2+b^2}\right] \quad (5)$$

where a refers to location parameter, b refers to scaling parameter which is experimentally set to 30. The subtraction of the moving objects and the background region can be achieved using the Cauchy distribution model at each pixel. For defining the background region at each pixel, the first type of the developed conditional model is used and $f_1(\Delta_t(x,y);\, a_1,b)$ probability can be expressed as follows:

$$f_1(\Delta_t(x,y);\, a_1,b) = \frac{1}{\pi}\left[\frac{b}{(\Delta_t(x,y)-a_1)^2+b^2}\right] \quad (6)$$

where a_1 is the location parameter of the first type of the developed conditional probability model and is calculated as below:

$$a_1 = \frac{\sum_{l=0}^{b} l x n_l}{\sum_{l=0}^{b} n_l} \quad (7)$$

Where b represents the scaling parameter and *l* represents the arbitrary gray level n within the absolute differencing image $\Delta_t(x,y)$ and n_l represents the pixel level corresponding to the arbitrary gray level. For the classification of moving objects at each pixel, the second type of developed conditional probability model $f_2(\Delta_t(x,y);\, a_2,b)$ is used and can be expressed as

$$f_2(\Delta_t(x,y);\, a_2,b) = \frac{1}{\pi}\left[\frac{b}{(\Delta_t(x,y)-a_2)^2+b^2}\right] \quad (8)$$

where a_2 is the location parameter of the second type of the developed conditional probability model and is calculated as below:

$$a_2 = \frac{\sum_{l=b+1}^{l_{max}} l x n_l}{\sum_{l=b+1}^{l_{max}} n_l} \quad (9)$$

where b represents the scaling parameter and *l* represents the arbitrary gray leven with in the absolute differencing image $\Delta_t(x,y)$,l_{max} represents the maximum gray level with in the absolute differencing image and $n_l$represents the pixel level corresponding to the arbitrary gray level. $\Delta_t(x,y)$and $n_l$represents the pixel number corresponding to the arbitrary gray level *l*.

Finally, the binary object binarization mask $D_t(x,y)$ can be obtained as follows:

$$D_t(x,y) = \begin{cases} 0, & if\ f_1 > f_2 \\ 1, & otherwise. \end{cases} \quad (10)$$

Notice that each pixel of $D_t(x,y)$ is equal to 0 when it belongs to the background region of the incoming video frame $I_t(x,y)$ and that each pixel of $D_t(x,y)$ is equal to 1 when it belongs to moving objects in the incoming video frame $I_t(x,y)$.

EXPERIMENTAL RESULTS

This section explains the experimental results for our proposed BMM (Background matching model) based Cauchy distribution (BMMC) model. We use a video sequence to test the method by qualitative visual inspection. On the other hand quantitative measurement can also be done using four design metrics called Recall, Precision, F_1, and Similarity. These design metrics specify the detection accuracy of our proposed method.

Finally, the time consumption of each method is calculated in terms of performance evaluation.

Qualitative Measurement

The qualitative measurement can be explained here with a video sequence named "hallway". At three different frames motion masks with their ground truths are represented. the below fig 3(a) represents three different frames in input video sequences and fig 3(b)and (c) represents their ground truths and motion masks. The ground truths at each frame are taken as ideal case or reference images for Cauchy distribution. The slight oscillations of the camera caused by wind, gradual illumination changes, because of changes in cloud cover or location of the sun many natural phenomenon of the outdoor environments may act as complexity of processing the obtained video sequence. For the indoor environments the detection rate is reduced when the moving object is slowing down or stopping. Fig. 5(a) represents the input video frame of background subtraction method and 5(b) represents corresponding output respectively. Here in background subtraction method only the moving targets can be detected by using the dynamic threshold. Where as in our proposed method motion masks are obtained with the scaling parameter. Because of the scaling parameter since it is experimentally fixed to 30 we can have limited no of frames but the motion masks can be generated effectively with perfect background subtraction which can be done by taking the absolute difference values of Cauchy distribution. The qualitative and quantitative measurements are taken for our proposed method but it cannot be done in other case. The next stage of this paper explains about quantitative measurements as below.

Quantitative Measurement

The quantitative measurement is also important to analyze the detection accuracy of the video surveillance systems. The accuracy can be calculated experimentally and results are plotted in tabular column for a different input video sequence like "Hall", "traffic". The accuracy metrics are defined below.

Recall metric: The percentage of necessary true positives in the detected binary object mask can be evaluated as below:

$$\text{Recall} = \frac{t_p}{t_p + f_n} \tag{11}$$

Where $t_p$is total number of true-positive pixels, where f_n is total number of false-negative pixels and (t_p+f_n) is total number of true-positive pixels in the ground truth.

Precision: The percentage of unnecessary true positives can be evaluated using the precision metric

$$\text{Precision} = \frac{t_p}{(t_p + f_p)} \tag{12}$$

Where $f_p$is total number false-positive pixels and $(t_{p+}f_n)$ is total number of true positive pixels in the detected binary motion mask.

Table I. *Quantitative measurement of BMMC method.*

Test sequence	Design metric	BMMC result
HALL	Similarity	0.3411
	F_1	0.5087
	Precision	0.8972
	Recall	0.3601
Traffic	Similarity	0.349
	F_1	0.437
	Precision	0.349
	Recall	0.705
Car	Similarity	0.78
	F_1	0.313
	Precision	0.55
	Recall	0.23

Since Recall and Precision individually measure the percentage of necessary and unnecessary true-positive pixels, the excess true-positive pixels may be associated with high Recall, and missing true-positive pixels may be associated with high precision. To facilitate an effective accuracy measurement, the harmonic means of recall and precision can be achieved by using F_1, and Similarity metrics, which can be expressed as follows:

F_1 = 2(Recall) (Precision)/ (Recall+Precision). (13)

Similarity = $t_p/(t_p+f_p+f_n)$ (14)

Note that all design metrics range from 0 to 1, with higher values indicating greater accuracy. Table I lists the average accuracy rate of our proposed BMMC method with two test video sequences.

Fig3. *(a) 1st Frame, (b) 9th frame, (c) 11th frame*

Fig4. *Ground truths of the frames*

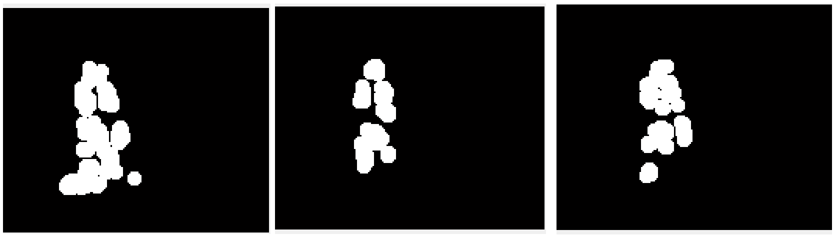

Fig5. *Extracted Cauchy distributed backgrounds*

Fig6. *Processed target from the extracted background*

CONCLUSION

In the proposed BMMC each possible background pixel can be selected to accurately update the adaptive background model at every frame. Furthermore, the proposed method also applies the conditional Cauchy models to detect moving objects instead of the single threshold function, thus generating the exact motion mask. Compared with other methods, we have verified that the proposed method attains the most satisfactory outcome based on qualitative evaluation and quantitative measurement. Moreover, performance evaluation also indicates that the proposed method can be easily implemented in embedded systems with limited resources for the vision oriented application of the intelligent transportation system.

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