Various Techniques for Detection of Moving Object

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***Abstract* --- In this paper, there are many techniques(like Background Subtraction, Optical Flow, Frame Differencing, Block Matching etc.) used for detection of moving object. In Background Subtraction, there are further two sub techniques that are Gaussian of Mixture and Approximate Median. These all techniques are used for different application and different purpose. Each of this technique has its own merits and demerits. Moving object detection is essential for real-time surveillance and it has variety of uses such as video communication and compression, medical imaging, indoor/outdoor security, real-time crime detection, Traffic monitoring.**

***Keywords*--- Moving Object, Gaussian Mixture Model, Optical Flow, Background Subtraction, Block Matching, Approximate Median.**

I. INTRODUCTION

Moving object detection is the 1st step in the video analysis. It has variety of uses such as real-time surveillance, video communication and compression, medical imaging, indoor/outdoor security, real-time crime detection and traffic monitoring.

There are total five moving object detection techniques like Background Subtraction, Optical Flow, Frame Differencing and Block Matching. In Background subtraction further divided two techniques Gaussian mixture model and Approximation median.

Frame differencing method is easy to implement, but many times it gets poor job of extracting the complete shapes of certain types of moving objects. It has less computational complexity.

The **Mixture of Gaussians** method was proposed by Friedman and Russell. It is widely used for the background modeling. Stauffer presented an adaptive background mixture model by a mixture of K Gaussian distributions.

Optical flow method can detect the moving object even when the camera moves, but it also needs more time for its computational complexity. It is also very sensitive to the noise. The motion area usually appears quite noisy in real

A **Block Matching Algorithm** (BMA) is a way of locating matching blocks in a sequence of digital video frames for the purposes of motion estimation. The purpose of a block matching algorithm is to find a matching block from a frame **i** in some other frame **j**, which may appear before or after **i**. This can be used to discover temporal redundancy in the video sequence, increasing the effectiveness of inter frame television standards conversion.

Basically, Median filtering is used in **Approximate Median**. In median filtering, the previous N frames of video are buffered, and the background is calculated as the median of buffered frames. Then, the background is subtracted from the current frame and thresholded to determine the foreground pixels [3]. Median filtering has been shown to be very robust and to have performance comparable to higher complexity methods. However, storing and processing many frames of video requires large amount of memory. This can be reduced somewhat by storing and processing frames at a rate lower than the frame rate thereby lowering storage and computation requirements at the expense of a slower adapting background.

II. DETECTION METHODS

A. Frame Differencing

Frame differencing is the simplest form of the background subtraction. The current frame is subtracted from the previous frame. The difference in pixel values for a given pixel is greater than a threshold Ts, the pixel is considered as a part of the foreground [2].

$$| frame_i - frame_{i-1} | > T_s \qquad (1)$$

B. Gaussian of Mixture

The Gaussian mixture model(GMM) is a single extension of the Gaussian probability density function(Gaussian PDF). The single Gaussian background model uses individual Gaussian distribution to express background, can process the simple scene with small change and secular change[10]. But it's not applicable to those scenes with big change or sudden change of background, or the background pixel value is multimodal distributed (like small and repeatedly motion). Because then the background changes fast, its distribution is not a transition from a relatively steady unimodal distribution to another[11]. As the GMM can approximate any smooth shape of the density distribution, It is often used in image processing in recent years for good results. Suppose the Gaussian mixture model consists of and the combination of Gaussian probability density function, the Gaussian probability density function of each has its own standard deviation, mean and weight. The weights can be interpreted by the corresponding Gaussian model of the frequency, they more often appear in the Gaussian model the higher the weight. The higher frequency of occurrence, then find the maximum weight on the Gaussian probability density function. Finally, we get the Gaussian probability density function of the means pixel value is background image [5].

***1. Background model*:** Background subtraction is one of the most common methods of object segmentation. This process contains two steps:

Background and Update model [6]. The basic concept of the Gaussian mixture model is as long as the number of Gaussian of mixtures, an arbitrary distribution can be in any of the precision is mixed with a weighted average of Gaussian approximation.

***2. Background update*:** The known algorithms, if it is not updated, the step operation time will be very long, we must use the iterative method to update the standard deviation, mean and the weight to reduce the time required. In next steps before must set the basic parameters, as the number of Gaussian components, Number of background components are, Positive deviation threshold , learning rate between 0 to 1.

Although the computational complexity of the GMM is high but it can provide better results. If new entrants cannot be matched to any pixel of a Gaussian probability density function, update the pixel value of mean, then initialize the standard deviation and the weights [4][6]

3. Algorithm of Gaussian Mixture Model:

For the desired result, following steps were adopted and background subtraction methods are used for better understanding:

Step-1 Initially, we compare each input image of pixels to the mean 'µ' of the associated components. If the value of a input image's pixel is close enough to a chosen component's mean, then that component is considered as the attached component. In order to be a matched component, the difference between the pixel and mean must be less than compared to the component's standard deviation scaled by factor D in the algorithm.

Step-2 In the next step updates the mean, Gaussian weight and standard deviation to reflect the new obtained pixel values. In relation to non-matched components of the weights 'w' decreases whereas the standard deviation and mean stay the same. It is dependent upon the learning component 'p' in relation to how fast they change.

Step-3 In the third step, we identify which components are parts of the background model. To do this a threshold value is applied to the component weights 'w'.

Step-4 In the final step, we determine the foreground pixels. Here the pixels that are identified as foreground do not match with any components determined to be the background.

4. General formula of Gaussian Mixture Model:

The weighted sum of the means of the component densities. Where be the variable which represents the current pixel in frame, K is the number of distributions, and t represents time is an estimate of the weight of the i^{th} Gaussian in the mixture at time t, is the mean value of the i^{th} Gaussian in the mixture at time t, is the covariance matrix of the i^{th} Gaussian in the mixture at time t.

A Gaussian mixture model can be formulated in general as follows:

$$\mathbf{P}(X_t) = \sum_{i=0}^{k} \omega_{i,t}\, \eta(X_t; \mu_{i,t}, \Sigma_{i,t}) \qquad (2)$$

Where, obviously,

$$\sum_{i=1}^{k} \omega_{i,t} = 1 \qquad (3)$$

$$\mu_t = \sum_{i=1}^{k} \omega_{i,t}\mu_{i,t} \qquad (4)$$

That is, the weighted sum of the means of the component densities. Where be the variable which represents the current pixel in frame, K is the number of distributions, and t represents time (i.e., the frame index), ω is an estimate of the weight of the i^{th} Gaussian in the mixture at time t, µ is the mean value of the i^{th} Gaussian in the mixture at time t, ∑ is the covariance matrix of the i^{th} Gaussian in the mixture at time t.

C. Block Matching Algorithm

The block matching algorithm (BMA) is a standard technique for encoding motion in video sequences [8]. It aims at detecting the motion between two images in a block-wise sense. The blocks are usually defined by dividing the image frame into non-overlapping square parts. Each block from the current frame is matched into a block in the destination frame by shifting the current block over a predefined neighborhood of pixels in the destination frame. At each shift, the sum of the distances between the gray values of the two blocks is computed. The shift which gives the smallest total distance is considered the best match.

In the ideal case, two matching blocks have their corresponding pixels exactly equal. This is rarely true because moving objects change their shape in respect to the observer's point of view, the light reflected from objects' surface also changes, and finally in the real world there is always noise. Furthermore, from semantic point view, in scenes containing motion there are occlusions among the objects, as well as disappearing of objects and appearing of new ones.

Despite the problems of pixel by pixel correspondence, it is fast to compute and is used extensively for finding matching regions. Some of the most often used matching criteria based on pixel differencing are mean squared distance (MSD), mean absolute distance (MAD) and normalized cross-correlation(NCC) [7].

Block matching techniques can be divided into three main components as shown in Figure 1: block determination, search method and matching criteria.

The first component, block determination, specifies the position and size of blocks in the current frame, the start location of the search in the reference frame, and the scale of the blocks. We focus on fixed size, disjoint blocks spanning the frame, with initial start location at the corresponding location of the block in the reference frame. In tracking, a predictive method may be used In tracking, a predictive method may be used to improve the start location of the search.

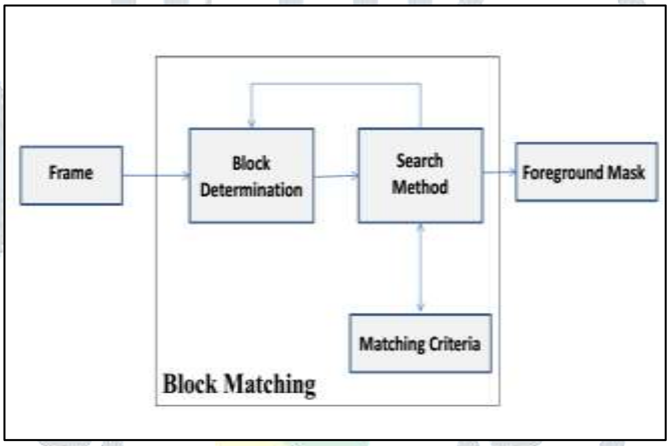

Figure 1: Block Matching Flowchart

The search method is the second component, specifying where to look for candidate blocks in the reference frame. A fully exhaustive search consists of searching every possible candidate block in the reference frame. This search is computationally expensive and other search methods have been proposed to reduce the number of candidate blocks and/or reduce the processing for all candidate blocks. In this report, we concentrate on search methods that reduce the number of candidate blocks.

The third component is the matching criteria. The matching criteria are a similarity metric to determine the best match among the candidate blocks. In faster search methods, the best match so far will also determine the direction of the search (choice of next candidate blocks).

The motion vectors are fed to the block determination to implement multi resolution blocks. A coarse to fine resolution of the blocks is generated. The start location of the search at each resolution is the location of the best match (motion vector) from the previous coarser resolution.

The implementation of block matching using components allows for flexibility; interchanging components produces a large variety of block matching techniques. Based on the application, components which provide the best results can be chosen with ease.

D. Optical Flow

The optical flow describes the direction and time rate of pixels in a time sequence of two consequent images. A two dimensional velocity vector, carrying information on the direction and the velocity of motion is assigned to each pixel in a given place of the picture.

For making computation simpler and quicker we may transfer the real world three dimensional (3-D+time) objects to a (2-D+time) case. Then we can describe the image by means of the 2-D dynamic brightness function of location and time I(x, y, t).

Provided that in the neighborhood of a displaced pixel, change of brightness intensity does not happen along the motion field, we can use the following expression.

$$I(x,y,t) = I(x+\delta x, y+\delta y, z+\delta z) \qquad (5)$$

Using Taylor series for the right hand part of the (3) we obtain

$$I(x+\delta x, y+\delta y, z+\delta z) = I(x,y,t) + \frac{\partial I}{\partial x}\delta x + \frac{\partial I}{\partial y}\delta y + \frac{\partial I}{\partial z}\delta z + H.O.T \qquad (6)$$

From (5) and (6), with neglecting higher order terms (H.O.T.) and after modifications we get

$$I_x.V_x + I_y.V_y = -I_t \qquad (7)$$

or in formal vector representation

$$\nabla I.\vec{v} = -I_t \qquad (8)$$

Where ∇I is so-called the spatial gradient of brightness intensity and v vector is the optical flow (velocity vector) of image pixel and I_t is the time derivative of the brightness intensity.

Equation (6) is the most important equation for optical flow calculation and is called 2-D Motion Constraint Equation or Gradient Constraint. It represents one equation with two unknown quantities.

Optical flow estimation is computationally demanding. At present there are several groups of methods for its calculation. All the methods come from (7) and consequently the presumption of conservation of brightness intensity. In this article our interest is concentrated in the differential methods.

The optical flow determination is solved by the calculation of partial derivatives of the image signal.

E. Approximation Median

Assuming that the background is more likely to appear in a scene, we can use the median of the previous n frames as the background model [1].

$$B(x,y,t) = median\{T(x,y,t-i)\}\ldots\ldots\ldots$$

$$|I(x,y,t)-median\{I(x,y,t-i)\}| > Th\ldots\ldots$$

$$Where\ t \in \{0,\ldots\ldots, n-1\}. \qquad (9)$$

III. COMPARATIVE STUDY OF OBJECT DETECTION METHODS.

Method		Accuracy	Computational Time	Comments
Background Subtraction	Gaussian of Mixture	Moderate	Moderate	+ Low memory requirement - It does not manage with multimodal background
	Approximate Median	Low to Moderate	Moderate	+ It does not require sub sampling of frames for creating an adequate background model. -It computation requires a buffer with the recent pixel values
Optical Flow		Moderate	High	+ It can produce the complete movement information - Require Large amount of calculation
Frame Differencing		High	Low to Moderate	+ Easiest method. Perform well for static background. - It require a background without moving objects

Table 1 Comparative study of object detection methods

IV. CONCLUSION

In this paper, we have given all the moving object detection techniques. All this methods have merits and demerits. In approximate median, median filter is used for remove the noise. Background differencing is the easiest method. Optical flow method is very useful for detecting moving object but its time complexity very high. Gaussian of mixture required low memory but it doesn't cope with multimodal background.

V. REFERENCES

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