Moving Object Detection with Fixed Camera and Moving Camera for Automated Video Analysis

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Abstract— Detection of moving objects in a video sequence is a difficult task and robust moving object detection in video frames for video surveillance applications is a challenging problem. Object detection is a fundamental step for automated video analysis in many vision applications. Object detection in a video is usually performed by object detectors or background subtraction techniques. Frequently, an object detector requires manual labeling, while background subtraction needs a training sequence. To automate the analysis, object detection without a separate training phase becomes a critical task. This paper presents a survey of various techniques related to moving object detection and discussed the optimization process that can lead to improved object detection and the speed of formulating the low rank model for detected object.

Index Terms— Object Detection, Soft Impute method, Markov Random Field, Temporal Differencing, Moving object extraction, background subtraction.
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1.INTRODUCTION

Automated video analysis is important for many vision applications [11]. There are three key steps for automated video analysis: object detection, object tracking, and behavior recognition. As the first step, object detection aims to locate and segment interesting objects in a video. Then, such objects can be tracked from frame to frame, and the tracks can be analyzed to recognize object behavior. Thus, object detection plays a critical role in practical applications.

The primary goal of this paper is to critically discuss the various techniques for detecting moving objects methods in static and dynamic background in video. A second goal is to present a technique for formulating low rank model for detected object.

The rest of the paper is organized as follows: section 2 we discuss existing approaches for Moving Object Detection techniques, while section 3 discuss the proposed method for detecting object accurately and section 4 is summarized in the conclusions.

I. MOVING OBJECT DETECTION TECHNIQUE

Detection and extraction of moving object form a video sequences is used in various application like Video surveillance system, Traffic monitoring , Human motion capture, Situational awareness, Border protection and monitoring ,Airport safety.

Moving object can be detected from video sequences of either a fixed or a moving camera.

The main purpose of foreground detection is to distinguishing foreground objects from the stationary background. Detection of moving objects in video images is very important. The automatic detection of moving objects in monitoring system needs efficient algorithms. The common method is simple background subtraction i.e to subtract current image from background. But it can't detect the difference when brightness difference between moving objects and background is small. The other approach is to use some algorithms such as color based subtraction technique.

There are several methods to detect moving objects, which are given below:

A. Optical Flow Method
Optical flow method is a complex and bad anti-noise performance, and it cannot be applied to real-time processing without special hardware device. [14] Proposes an automatic extraction technique of moving objects using x-means clustering. In this proposed method, the feature points are extracted from a current frame, and x-means clustering classifies the feature points based on their estimated affine motion parameters. A label is assigned to

the segmented region, which is obtained by morphological watershed, by voting for the feature point cluster in each region. The labeling result represents the moving object extraction.

B. Consecutive Frames Subtraction

Consecutive Frames Subtraction is a simple operation, realizes easily and has strong adaptability on the dynamic changes in the environment. But it cannot be completely extracted moving targets. [15] proposes a novel method for extracting moving objects from video sequences, which is based on Gaussian mixture model and watershed, is proposed where first the difference between neighboring frames is calculated and is described by a Gaussian mixture model, then divided into moving areas and background by improved Expectation-Maximization (EM) algorithm.

C. Background Subtraction

Background subtraction is a common method for detecting moving objects and it has been widely used in many surveillance systems, but it is yet a difficult problem to distinguish moving objects from backgrounds when these backgrounds change significantly. Separating foreground from background in a video sequence is one of the most fundamental tasks in many applications of computer vision. To detect moving objects, each incoming frame is compared with the background model learned from the previous frames to divide the scene into foreground and background. Therefore, background modeling has been actively investigated in the past decade. The difficulty encountered in background modeling is that the outdoor backgrounds are usually non-stationary in practice. Broadly speaking, there are two categories of online methods to model the background. The first one models the background using a single model per pixel, whereas the second one employs multiple models per pixel. Background subtraction is a widely used approach for detecting moving objects from static cameras [16].

The four major steps in a background subtraction Algorithm are:

- Preprocessing

- Background Modeling

- Foreground Detection

- Data validation
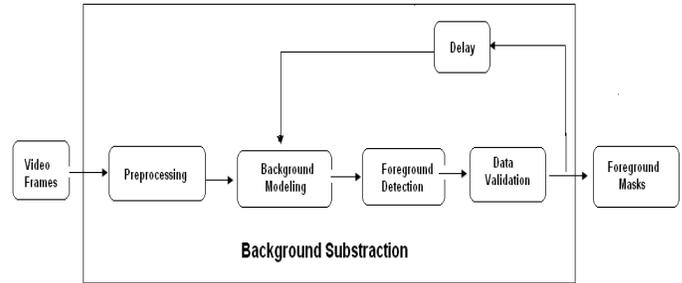
Figure 1.Illustration of Background Subtraction

In background subtraction, the general assumption is that a background model can be obtained from a training sequence that does not contain foreground objects.
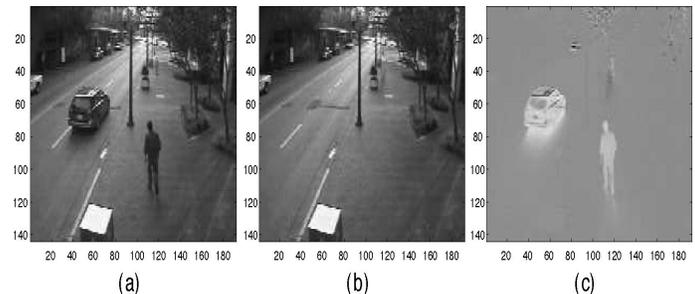
Figure 2. Decomposition-based background subtraction: (a) an input image with objects, (b) reconstructed image after projecting input image onto the, (c) difference image.

Color and Edge Information:

Jabri, et al. [4] proposed an approach in which background modeling and subtraction approach are used to detect a human in the video images. This approach is used to segment the person from the background by computing the mean image for all video sequences. The incoming frame is subtracted from the mean image to identify the pixels which have changed the color. However, the problem with this approach is both the color and edge channel are subtracted separately before finding the result and, as a consequence, the computational time increases.

Standard Subtraction:

The method developed by Davis and Taylor [5] is a motion-based method for differentiating normal walking movements at multiple speeds when atypical or non walking locomotion is involved. Human walking movements are detected using low level regularities and constraints. The person's shape in each video frame is extracted with standard background subtraction. This approach locates the head, waist and feet using the W4 approach [6]. Standard subtraction techniques, which use RGB pixel differences, dilations and removal of small pixel region, are employed. The centroid of the outline pixel is called the head pixel, while the mean value of silhouette pixels in the torso region is called the waistline. The waistline is divided into two halves in order to locate information relating to the

feet. Dynamic regularity features are calculated using cycle time, stance/swing ratio and double support time. Dynamic regularity features are independent of the camera position, but this approach uses view-based constraint of extension angle, which is suitable for non-walking locomotion and not for other regular locomotion's.

Object Extraction:

The algorithm proposed by Yoginee, et al. [13] has moving object segmentation, blob analysis and tracking. Blob analysis is used to count the vehicle from which the speed and flow are calculated. Boundary Block Detection (BBD) algorithm is used for moving object detection by identifying the blocks which contain the moving objects boundaries. The system requires the model background with no moving objects and scene which contain moving objects. The system finds the boundary of the moving objects and the number of moving objects from a given video scene. Aviread function [13], is used to extract all frames in the video. Background subtraction extracts the object, while the pixels of the background model image are used as threshold. All images are divided into two parts, viz., background and foreground in binarization. The new video frame was subtracted from those background images, if the pixel difference is higher than the threshold, that images are foreground or object. If the pixel significantly differs from the background image, then the pixel is marked as a moving object. Each image frame must update the threshold level. To count the moving object flow, the algorithm tracks each vehicle within successive image frames. This algorithm works only for the videos obtained from fixed cameras and which has the normal background and stable videos. The algorithm can be modified to work on complex background and videos that are not stable. In addition, the performance can be improved by using optimizing algorithm such as fuzzy logic and neural network.

Gaussian Mixture:

A Gaussian Model calculates each pixel-value from all the sample pixels' mean and variance. The model will set a lower bound and an upper bound that will eliminate pixels that are outside of the norm. If a video is to run for an extended period of time, the pixels' average will equal to the background's value unless the foreground object stays static. This is a common method for real-time segmentation of moving regions in frame sequences. Model Gaussians are updated using K-means approximation method. Each pixel is then evaluated and classified as a moving region or as a background.
Stauffer and Grimson [3] presented a novel adaptive online background mixture model that can robustly deal with lighting changes, repetitive motions, clutter, introducing or removing objects from the scene and slowly moving objects. Their motivation was that a unimodal background model could not handle image acquisition noise, light change and multiple surfaces for a particular pixel at the same time. Thus, they used a mixture of Gaussian distributions to represent each pixel in the model.

Temporal Differencing:

Temporal differencing method uses the pixel-wise difference between two or three consecutive frames in video imagery to extract moving regions. It is a highly adaptive approach to dynamic scene changes however, it fails to extract all relevant pixels of a foreground object especially when the object has uniform texture or moves slowly. When a foreground object stops moving, temporal differencing method fails in detecting a change between consecutive frames and loses the object.

Let Frame i represent the gray-level intensity value at pixel position i and at time instance n of video image sequence I, which is in the range [0, 255]. T is the threshold initially set to a pre-determined value. Lipton developed two frame temporal differencing scheme suggests that a pixel is moving if it satisfies the following:

$$| \text{ Frame i} - \text{Frame i-1}| > th$$

This estimated background is just the previous frame. It evidently works only in particular condition of objects speed and frame rate and very sensitive to the threshold.

This method is computationally less complex and adaptive to dynamic changes in the video frames. In temporal difference technique, extraction of moving pixel is simple and fast. Temporal difference may left holes in foreground objects, and is more sensitive to the threshold value when determining the changes within difference of consecutive video frames [2]. Temporal difference require special supportive algorithm to detect stopped objects.

Comparison of several popular methods for moving object detection:

Optical Flow method	Consecutive Frames Subtraction	Background Subtraction
Complex and bad anti-noise performance	simple operation, realizes easily	provides a moving object comprehensive and reliable Information
cannot be applied to real-time processing without special hardware device	has strong adaptability on the dynamic changes in the environment	very sensitive to the irradiation which is caused by dynamic scene changes
		Advantage of not requiring previous knowledge of moving objects such as shapes or movements **Disadvantage**cannot

		discriminate moving objects from backgrounds when these backgrounds change significantly

2. THE PROPOSED METHODS

In this section, it integrates the object detector and background subtraction in to the single process of optimization which can work efficiently for moving object detection.

Moving Object detection is the basic step for further analysis of video. Every tracking method requires an object detection mechanism either in every frame or when the object first appears from stationary background object.

When working with video data, it can be helpful to select a representative frame from video and the methods can be applied to the processing of all the frames in the video. The method computes the estimated foreground and background model of frame specified by rank.

To make the problem well posed, we have the following models to describe the foreground and the background model.

Notation:

In this paper, we use following notation. $I_j \in \mathbb{R}^m$ denotes the jth frame of video sequence, which is written as a column vector consisting of m pixels.the ith pixel in the jth frame is denoted as ij. $D=[\ I_1, I_2, \ldots \ldots I_n]\ \in\ IR^{m*n}$ is a matrix representing all n frames of a sequence. $B \in \mathbb{R}^{m \times n}$ is a matrix with the same size of D ,which denotes the underlying background image. $S \in \{0,1\}^{m \times n}$ is a binary matrix denoting the foreground support :

$$S_{ij} = \begin{cases} 0, & \text{if } ij \text{ is background} \\ 1, & \text{if } ij \text{ is foreground.} \end{cases} \quad \text{(1)}$$

Our objective is to estimate the foreground support *S* as well as the underlying background image *B*, from the given sequence *D*. The preprocessing model is common in both modules Detection moving objects from video sequence of a fixed camera and moving camera.

Preprocessing Model:

The input to the algorithm is a sequence of video frames which convert RGB to gray-level format. The algorithm produces a binary mask for each video frame. The pixels in the binary mask that belong to the background are assigned 0 values while the other pixels are assigned to be 1.

The preprocessing module performs basic steps to process the video frames for detecting object from video. As illustrate in Figure 3
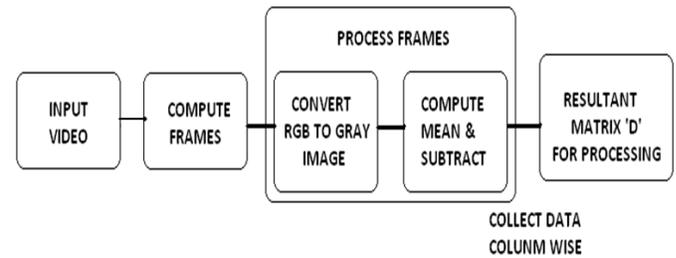
Figure 3.Framework for Preprocessing Module

The algorithm uses the Norms Matrix's which has same size as Matrix *D* of input sequences. Four norms of a matrix are used.

- $\|X\|_0$ Norm: Which contains all non-zero entries
$$\|X\|_0 = \sqrt{\sum i |Xi|}$$
- $\|X\|_1$ Norm: which computes for the difference between the two matrices and vectors.
$$\|X\|_0 = \sum i |Xi|$$
- $\|X\|_F$ Norm: which compute the sum of squared difference (SUD).
$$\|X\|_F = \sqrt{\sum ij |Xij|^2}$$
- Nuclear Norm: which compute sum of singular value.

Transform Matrix: In Transform matrix the input matrix 'D' is processed, is used to recover the values later if the values is missing or lost after processing the video. This is the input matrix for both modules Detection moving objects from video sequence of a fixed camera and moving camera.

The transform matrix finds the variation acquire in the sequence of frames, which first compute the middle frame, then process all frames from middle to first frame and then process middle to right frame because the assumption is that the most of the variation are occurs in video at middle part.

Detecting moving objects from video sequences of a Fixed Camera:

Background refers to a static scene and foreground refers to the moving objects. Objective is to estimate the foreground support as well as underlying background images.

Steps:
- Preprocessing [Moving Object And Static Background]
- Background Model
- Estimate Low Rank matrix for Background Foreground Model
- Estimate Low Rank matrix for Foreground

The following figure 4 shows the detecting moving object in static background.
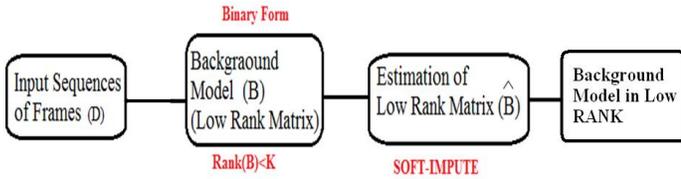
Figure 4 Detecting Moving Object In Static Background

The background intensity should be unchanged over the sequence except for variations arising from illumination change or periodical motion of dynamic textures.1 Thus, background images are linearly correlated with each other, forming a low-rank matrix B. The only Constraint on B is:

$$rank\ (B) <= K; \quad (2)$$

Where K is a constant to be predefined. Intrinsically, K constrains the complexity of the background model.

To formulate the background model, the SOFT-IMPUTE [10] method is used which produces a sequence of solutions for which the criterion decreases to the optimal solution with every iteration and the successive iterates get closer to the optimal set of solutions of the problem. SOFT-IMPUTE decreases the value of the objective function towards its minimum, and at the same time gets closer to the set of optimal solutions of the problem In many applications measured data can be represented in a matrix $Xm{\times}n$, for which only a relatively small number of entries are observed. The problem is to "complete" the matrix based on the observed entries, and has been dubbed the matrix completion problem.

 SOFT-IMPUTE iteratively replaces the missing elements with those obtained from a soft-threshold SVD. SOFT-IMPUTE algorithm , which makes use of the following lemma[] :

Lemma 1. Given a matrix Z, the solution to the optimization problem

$$\underset{Z}{\text{minimize}} \quad \frac{1}{2}\|W - Z\|_F^2 + \lambda\|Z\|_* \quad (3)$$

is given by $\check{Z} = \mathbf{S}_\lambda(W)$ *where*

$$\mathbf{S}_\lambda(W) \equiv UD_\lambda V' \quad with \quad D_\lambda = \text{diag}\,[(d_1-\lambda)_+,\ldots,(d_r-\lambda)_+], \quad (4)$$

UDV' *is the SVD of* W, $D = \text{diag}\,[d_1,\ldots,d_r]$, *and* $t_+ = \max(t,0)$.

Using Lemma 1,the optimal solution to can be obtained by iteratively using:

$$\hat{B} \leftarrow \Theta_\alpha(\mathcal{P}_{\hat{S}\perp}(D) + \mathcal{P}_{\hat{S}}(\hat{B})) \quad (5)$$

with arbitrarily initialized $\hat{B}$.

The foreground is defined as any object that moves differently from the background. Foreground motion gives intensity changes that cannot be fitted into the low-rank model of background. Thus, they can be detected as outliers in the low-rank representation. Generally, we have a prior that foreground objects should be contiguous pieces with relatively small size.

Algorithm: Background estimation using soft impute method.

Soft Impute :iterative soft threshold SVD to impute the missing values

Input : D=[$I_1,I_2,\ldots\ldots I_n$] €IR^{m*n}

Initialization:
'X': is incomplete matrix
'maxRank': is the desired rank in the constraint
'Omega':is the mask with value 1 for data and 0 for missing part

Steps:
```
if isEmpty(Z)
            z=x;
 end
if isEmpty(Omega)
       Omega=true(size(x))
    end
if isEmpty(maxRank)
            maxRank=-1;
end
Repeat
while(1)
       -c=x*omega+z*(1-omega)
       -apply the SVD(single value Decomposition)
       -d=diag(D)
       -index=find(d>alpha)
       -'z' recompute based on index
       -k=length(index)
Termination condition
       Repeat
       -if (k<maxRank && omega >0.0001)
             alpha=alpha+eta;
       else
             break;
       end
```
Output: smooth Background Model and masks for foreground model.
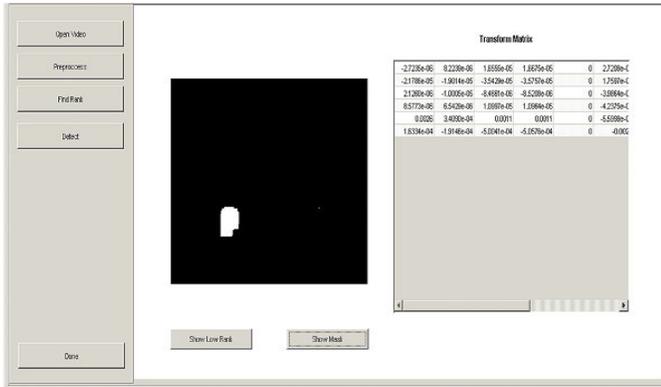
Figure 5 Mask for foreground Moving Object In Static Background

Result of soft impute method shows the mask for foreground and later this mask is used by MRF graph cut method ,for detecting the foreground in processing video.

Foreground Model Used The Markov Random Field with Graph Cut Method:

To compute the foreground model, Markov random field (MRFs) methods are used. Due to utilization of the relativity of every pixel of an image, the Markov Random Field (MRF) model is effective in solving the problem of detecting moving object under a complex background.

The Markov Random Fields (MRFs) [9] is statistical model, which used for restore the true image; images are often treated as realizations of a random process and MRFs to improve the accuracy of detecting foreground object. As illustrate in Figure 6:

Figure 6 Segmentation of foreground Moving Object In Static Background

Detecting moving objects from video sequences of a Moving Camera:

The above section is based on the assumption that the videos are captured by static cameras and background is static and the foreground is moving. In this section, we propose the method which handles the both background and foreground are moving which is caused by moving cameras.

The proposed method uses image registration for detection moving object in motion camera. The registration is a process which makes the pixel in two images precisely coincide to the same points in the video. Once registered the image can be combined or fused in a way that improve detection of foreground in motion camera.

In this method, we use dataset having object is moving in the video with motion background and also detect the outliers present in video sequences.
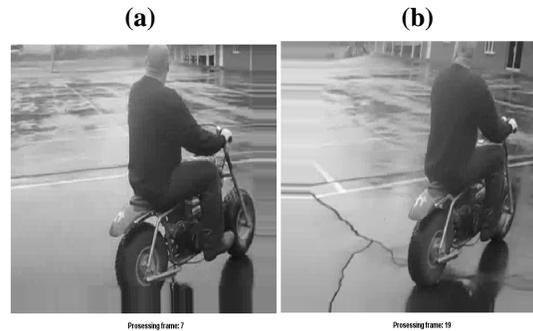
Figure 7. Moving object under motion camera (a) The processed frame 7, (b) the processed frame 19.

This case represents the most general scenario of motion because observer motion and object motion induce multiple coupled motion. As illustrate in Figure 8:
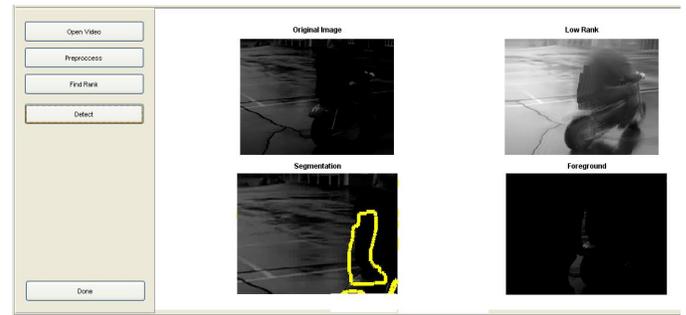
Figure 8. Segmentation of foreground Moving Object In Motion Background

3. CONCLUSION

In this paper, we discussed a variety of techniques to detect moving object in video frames. Amongst the methods reviewed, the background subtraction method; the subtraction of color and edge channels are performed separately before finding out the result. It is not robust against changes in illumination. It cannot detect non stationary background object such as swinging leaves, rain snow and shadow cast by moving object. Furthermore, in this paper, we have proposed a single process of optimization which integrates the object detection and background learning which can be used to detect

the moving object accurately, such that the time and accuracy attributes can be improved.

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