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# Effective Method of Detecting and Tracking of Moving Objects for a Video Surveillance System

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**ABSTRACT:** Video surveillance is the system of monitoring the behaviour, activities or other changing information for the purpose of influencing, managing, controlling or securing people. The video surveillance system has experienced a number of technology shifts to reach the necessary requirements. The present video surveillance system includes observation from a distance by means of electronic equipments such as closed-circuit television cameras or interception of electronically transmitted information such internet traffic or phone calls. The present surveillance system also includes relatively low-technology methods such as human intelligence agents and postal interception. This paper demonstrates new age technology methods of background subtraction which include Gaussian mixture and Kernel Density Estimation and tracking method include Silhouette tracking approach. In this paper the system is being developed to meet increasing demands such as speed, storage and better image quality.

**KEYWORDS**: Gaussian Mixture, Kernel Density Estimation, Silhouette Tracking

## I. INTRODUCTION

Video surveillance [1] which forms one of the fundamental components of security system, depends more on object detection and tracking. Video surveillance is basically used for monitoring and analyzing video sequences for the purpose of checking the behaviour, activities and other certain information in a video sequence [2]. Moving object detection and tracking is an important research topic in computer vision field, and is also the basis for video surveillance. Background subtraction is a method used for detecting moving objects in videos from static camera. Tracking people's motion is an important issue in video analysis. For example counting people in a monitored area, determining time spent in the area by individual persons. It can be also used as a preliminary step for more detailed analyses performed by video surveillance systems, such as learning and recognition of human actions. The presented algorithm is depends on feature paths. It employs the fact that paths corresponding to a motion of a single object are close to each other spatially and overlap in time. Therefore, the paths are clustered in a way that each cluster gathers elements corresponding to a single person.

The logic of this approach is that detecting moving objects from the current frame and reference frame with a fixed threshold value. The approaches used in this paper aim to maximise speed and limit memory requirements aiming to achieve highest possible accuracy under possible circumstances. The most important objective of this survey paper is to determine the various methods in static and moving object detection and as well as tracking of moving objects. The method reviewed in the following in moving object detection and tracking in video image includes Mixture of Gaussians, Kernel Density Estimation (KDE) and silhouette tracking approach.

 

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## II. RELATED WORK

### 1) BACKGROUND SUBTRACTION METHODS

#### A) Mixture Of Gaussians

Sometimes the change in background object is not permanent and takes place at a faster rate than that of the background update. Some of the examples like raining, snowing and watching sea waves. In such instance single valued background is not a suitable model.

Stauffer and Grimson [3] came up with adaptive background mixture model that can cope with multiple background objects. The adaptive background mixture model proposed can be more clearly defined as it gives the description of background and foreground values.

Stauffer and Grimson [3] in background adaptive mixture model provide the probability of observing certain pixel value, x, at time t by means of mixture of Gaussians:

$$\mathbf{P(x_t) = \sum_{i=1}^{k} \omega_{i,t}\, \eta\, (x_t - \mu_{i,t}, \Sigma_{i,t})} \qquad \textbf{(1),}$$

Where **k** is the Gaussian distributions considered to report only one of the observable background or foreground objects. Gaussian involve two or more variable quantities such as red, green, blue values. If these variables are considered to be independent, then the co-variance matrix **($\Sigma_i$),** simplifies to diagonal. If the standard deviation for the three channels are considered to be same then it further reduces to simpler **$\sigma^2_i I$**.

For (1) to become a model of background alone a basis is required to provide distinction between foreground and background distributions. The presumption is higher and more close packed the distributions is the more likely to belong to the background.

$$\sum_{i=1}^{B} \omega i > \mathrm{T} \qquad \textbf{(2),}$$

Where T is a assignment threshold accepted as background. For each frame time t, there are two problems that must be simultaneously solved a) assigning the new observed value, $x_t$, to the best matching distribution and b) estimating the updated model parameters. These two algorithms can be solved by an algorithm called expectation maximization (EM) working on the buffer of last n frames. Since this algorithm is extremely costly, the matching is approximated in these terms:

$$\mathbf{(x_t - \mu_{i,t})/\sigma_{i,t} > 2.5} \qquad \textbf{(3)}$$

The first in ranking order is accepted as a match for $x_t$. Furthermore other parameters are updated only for this matching distribution and by using simple on-line cumulative averages. If no match is found, then the last ranked distribution is replaced by a new one centred in $x_t$ with low weight and high variance.

#### B) Kernal Density Estimation.

An approximation of the background probability density function (pdf) can be given by the histogram of the most recent values classified as background values. Since the number of samples is limited such an approximation suffers certain disadvantages: the histogram provides poor modelling of true unknown pdf, with the “tails” of the true pdf often missing. To overcome such issues, Elgammal et al. [4] have proposed to model the background distribution by a non-parametric model based on Kernel Density Estimation (KDE) on the buffer of the last n background values, which guarantees smooth and continuous version of histogram.

Background probability density function is given as a sum of Gaussian kernels centered in the most recent n background values, $x_i$

$$\mathbf{P(x_t) = 1/n \sum_{i=1}^{n} \eta(x_t - x_i, \Sigma_t)} \qquad \textbf{(4)}$$

Each Gaussian reports a main “mode” of the pdf and is updated over time; instead, each Gaussian describes just one sample data, with n in the order of 100, and Z; is the same for all krenels.

Model update [4] is obtained by simply updating the buffer of the background values in fifo order by selective update in this way, “pollution” of the model by foreground values is prevented. However, complete model estimation also requires the estimation of $\Sigma_t$. This is a key problem in KDE.

The model proposed [4] in Non- parametric model for background subtraction, is actually more complex than what outlined so far. First, in order to address the issue of the time scale, two similar models are concurrently used, one for long-term and the other for short-term memory. Second, the long-term model is updated with a blind update mechanism so as to prevent undesired exclusion from the model of incorrectly classified background pixels.

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Furthermore, it addresses explicitly the problem of spatial correlation in the modelling of values from neighbouring pixel locations as described.

**2) TRACKING**

**SILHOUETTE TRACKING APPROACH**

Objects might have complicated shapes, as an example, hands, head, and shoulders that can't be represented by easy geometric shapes. Silhouette primarily based ways offer associate degree correct form description for these objects. The goal of a silhouette primarily based object tracking [5] is to search out the thing region in every frame by suggests that of associate degree object model generated victimization the previous frames. This model is within the style of a color bar graph, object edges or the thing contour. We have a tendency to divided silhouette trackers into 2 classes, namely, shape matching and contour following.

- **Shape Matching**

Shape matching [6] approaches look for the thing silhouette within the current frame. form matching performance is comparable to guide primarily based following in kernel approach. Another approach to form matching is to search out matching silhouettes in 2 consecutive frames. Detection supported Silhouette is administered by background subtraction. Models object square measure within the style of density functions, silhouette boundary, object edges.

- **Contour following**

Contour following [7] approaches evolve associate degree initial contour to its new position within the current frame by either victimization the state house models or direct decrease of some energy purposeful

## III. CONCLUSION

This paper presents a review on most used background subtraction methods. This paper provides algorithms that is based on speed, accuracy and memory requirements which helps the user to choose suitable method for a given application in a predominant way. Methods such as Mixture of Gaussians and Kernel Density Estimation demonstrate to be very good model of correctness. KDE has high memory requirements which might stop easy execution on low-memory devices. In Silhouette tracking method, object is tracked by silhouette by calculating the object region in consecutive frames.

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