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EFFICIENT BACK GROUND SUBTRACTION USING ADAPTIVE SGMM

Aiswarya Muralidharan[1] ,S.Sivakumar[2],

Abstract: Background subtraction is one of the key techniques for automatic video analysis, especially in the domain of video surveillance because of their ability to cope with many challenging characteristic for surveillance systems in real time with low memory requirements. Background subtraction methods with respect to the challenges of video surveillance suffer from various shortcomings. To address this issue, first identify the main challenges of background subtraction. In this paper, we present a study of some relevant GMM approaches and analyze their underlying assumptions and design decisions. System is able to hold static foreground regions in the foreground, while correctly incorporating into the background model uncovered background regions.

Keywords: background initialization, background subtraction, change detection, GMM, SGMM

I.INTRODUCTION

The change detection is a task used as a first step in many computer vision applications such as video surveillance, medical diagnosis or human-computer interaction. In an image sequence, our aim is to identify for each frame the set of pixels that are significantly different from the previous frames. The requirements and constraints of the detection algorithm are different for different applications. In this paper change detection has been extensively used in order to segment foreground objects from the background. Foreground objects are associated between frames in order to perform a scene analysis and detect events of interest. The parts of the scene which are normally observed are considered as background. Therefore, it is assumed that the background can be well described by means of a statistical model, the background model [2].

Background subtraction algorithms use a model of the static scene, the background model, to distinguish between background and foreground in video sequences.

Aiswarya Muralidharan :ME Communication system ,Department of Electronics and communication ,Sri shakthi institute of engineering and technology, Coimbatore ,India
S.Sivakumar: Assistant professor, Department of electronics and communication,Sri shakthi institute of engineering and technology, Coimbatore,India

There have been many different proposals for the task of background subtraction Among them, Gaussian Mixture Models (GMMs) have proves outstanding suitability in the surveillance domain because of their ability to achieve many of the requirements of a surveillance system, e.g. adaptability and multimodality, in real-time with low memory requirements [3]. GMMs model the history of each pixel by a mixture of K Gaussian distributions, which are updated by means of an Expectation Maximization (EM)-like algorithm. Based on this model, pixels are classified as background or foreground. The process of segmentation of foreground objects by detecting the changes with reference to a background model is called as background subtraction.

Segmentation result has been improved by incorporating region level analysis in the background model. The frame of a video sequence can be analysed at two levels using a two layered system. A two-layered region classification system which is used to detect regions that should be specially handled because of belonging to either static foreground regions or uncovered background regions[1]. The information provided by the region analysis layer is then fed-back to the pixel layer in order to achieve a better model of the empty scene. The main task of a BS is to compare an input frame against a background model. It describes backgrou nd areas of the scene and often described by distribution of features such as colour. Foreground detection determines which areas of image belong to foreground class with similarity of input frame and background model and it creates foreground mask.

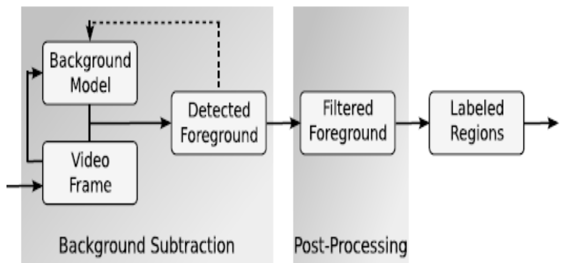

Fig 1:Back Ground Subtraction With Preprocessing

The two layered system analyses the video frame at two levels: pixel level and region level. At former level pixel classified on the result obtained by subtracting the two complementary background

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model and later ,new static foreground regions are classified as static or removed objects. To avoid incorporation of static foreground objects in to the background model information are fed back at the pixel level. Foreground detection is used to determine the areas of image belonging to foreground class with respect to the similarity in input frame and background model.

II. GMM FOR BACKGROUND SUBTRACTION

Gaussian mixture model is the probabilistic method of background subtraction. Compared to state of art method it is more adaptable and multimodal compared to state of art method and require low memory[1]. In statistics, a mixture model is a probabilistic model for representing the presence of subpopulations within an overall population, without requiring that an observed data set should identify the sub-population to which an individual observation belongs. Formally a mixture model corresponds to the mixture distribution that represents the probability distribution of observations in the overall population. However, while problems associated with "mixture distributions" relate to deriving the properties of the overall population from those of the sub-populations, "mixture models" are used to make statistical inferences about the properties of the sub-populations given only observations on the pooled population, without sub-population identity information. Some ways of implementing mixture models involve steps that attribute postulated sub-population-identities to individual observations (or weights towards such sub-populations), in which case these can be regarded as types of unsupervised learning or clustering procedures. However not all inference procedures involve such steps. Mixture models should not be confused with models for compositional data, i.e., data whose components are constrained to sum to a constant value (1, 100%, etc.). However, compositional models can be thought of as mixture models, where members of the population are sampled at random. Conversely, mixture models can be thought of as compositional models, where the total size of the population has been normalized to 1[1].

In this, pixel is modelled by a mixture of K Gaussian distributions and background model used to estimate the probability of a given pixel X_t at time t

$$P(Xt) = \sum_{k=1}^{K} \omega k N(Xt, \mu k, \textstyle\sum_k) \quad (1)$$

where ωk are the weights associated to each of the modes $k \in \{1 \ldots K\}$ describing a pixel, and $N(X t, \mu k, \sum_t))$ is a normal density of mean μk and covariance matrix $\sum_k$., which is usually assumed to be the diagonal matrix $\sigma_2 k\ I$ ..[1] The components are sorted according to their relevance and the background model is approximated by the first B components such that

$$B = argmink._k\ (\textstyle\sum_{k=1}^{K} \omega k > T) \quad (2)$$

Where $B \leq K$ and T indicates threshold indicating minimum portion of data which is assumed to be background. Sorting is done by means of a sorting criterion S_k in descending order. Background is described by means of high weight and small variance. GMM method is necessary because the background subtraction regarding the sequence lies on foreground and background pixels. The pixel based system lies on decision regarding the foreground and background. After decision making the object has to be tracked and the tracking process requires some knowledge about the appearance of object to be tracked. In cases we are unaware about the foreground object then it's defined by a uniform distribution and set a threshold to differentiate background from foreground.

III.PROPOSED METHOD

The Gaussian mixture model is a statistical method which defines the mean and variance of the system and the system having less error clarification .In this paper we are adapting to a Subspace Gaussian mixture model(SGMM) which defines the accurate foreground segmentation compared to GMM. In the existing method defined above, estimated the video sequence by defining its mean and standard deviation. This creates the deviation and pixel differentiation which is same in both the technique. The subspace Gaussian mixture model follows the same mathematical formulation as that of GMM .In GMM the video sequences are converted from the RGB to binary image directly and the estimation of foreground object is quite difficult. Foreground object obtained will be in grey format and its difficult to retrieve original foreground sequence. Compared to GMM, the video sequence have clarified foreground detection in SGMM and is achieved mainly due to efficient domain[2]. In SGMM the image sequence of video are converted from RGB to HSV space so that result clarified accordingly. The error will be reduced in later proposal. The algorithm is shown below:

1. Each input pixels are compared to the mean 'μ' of the associated components. If the pixel value is close to a chosen component's mean, then the matched component is obtained. To get the matched component the difference between the pixels and mean values should be less than compared to scaled factor of standard deviation. It is scaled by a factor d.
2. updation of Gaussian weight, mean and standard deviation (variance) to obtain the new calculated pixel value. In the case of non-matched components the weights 'w' decreases whereas the mean and standard deviation remains the same. It is dependent upon the learning component 'p' which changes as fast as the standard deviation and means changes
3. Identify which the components are belonging to the background model. To do this a threshold value is applied to the component weights 'w'.

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4. Determine the foreground pixels finally. Here the pixels which are identified as foreground don't match with any components that are defined to be the background.

In video sequence it's a complex process where they are spitted up to frames and the processing is done sequentially for n frames and finds the frame difference and segmentation is carried out and background object are completely removed.

Background subtraction not only remove background but also detect the foreground objects and define its parameter alone for applications like video surveillance and medical applications. In the proposed method we are defining a video and defining its features accordingly and carrying out Gaussian modelling in subspace.

IV.SIMULATION AND RESULTS

The simulation is done in MATLAB and make of Gaussian mixture modelling and the parameter are estimated and found out as defined in uniform distributed model. The process involved in this is listed as below and the diagrammatic representation is given below:

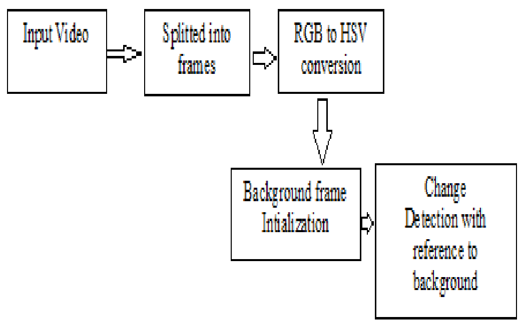

Fig 2: processing of change detection

The process involves reading a video file which is already updated in avi format and the video is uploaded in matlab window and it also process the video sequence .the processing of video sequence is mainly the splitting of video in to frames .this frames are splitted and stored to find out parameters .

Fig3(a&b):frames of input video

The video sequences are splitted as above there are n frames based on the video and these frames represent the image sequences and next step is the motion estimation of these frames and during this estimation all the parameter regarding Gaussian distribution has been found out by above equations 1&2.The image represented as an unsigned integer data type and processed in case of uploading. During motion estimation it got converted to a double data type. In motion estimation process, all the parameters are defined such as sigma; mu and threshold level .this threshold is set by us and also defines the process accordingly based on this level. This estimation also defines some morphological operation and the structuring element has been defined as disk and this causes an element to be chosen for morphological operation. The level of shadow is also defined in the process. The major process involved in this is the conversion of RGB to HSV space for the whole frames. Before the conversion the video is analysed fully and the represented for operation. Conversion of the space is done and Gaussian model is applied to the HSV space.HSV space represent hue, saturation and value and its actually an accurate domain than direct conversion to grey or binary. This direct conversion is not done in SGMM .Gaussian model is generated for each layer and for this each layer maximum deviation is defined. Mathematical formulation has been done to find out deviation by means of mu,sigma and then sorting level is also mentioned. This produces the deviation of the Gaussian distribution and also polar mean of the system. The pixel in 3 layers are same for a video sequence which are splitted in to different frames and each layer deviation and mean is calculated for each frame. The present frames are of same size and having 3 layers so it is computed for n frames. Considering one frame and defining its each layer to be in column manner for the computation process. This column conversion is done for taking difference between frames and this frame differencing requires the frame to be in equal matrix so they are adjusted to make it same matrix.

before this deviation is scaled in order to compare with mean and scaled one is stored in d. This scaling is done by means of comparison of the layers in a frame in all aspects such as shadow level and then angle difference in the image. Deviation is set as the difference of absolute values of threshold and then set compared it with the shadow. Now the image is in state where we detected the area of foreground by means of a threshold, ie above a threshold its identified as background and below as foreground. Segmented part with threshold should be labelled properly and this can be done by means of library gcut function and is labelled properly. At this stage the background is subtracted and thresholding cause the foreground object to be in irregular shaping and this threshold labelling provides the frames to be in a boundary. For this image morphological operation is performed such as erosion for edge smoothening and after it get smoothened ranking is done ie it will cause conversion of this labelled portion to largest component it will find out all non zero components and defines as a binary image and is shown below:

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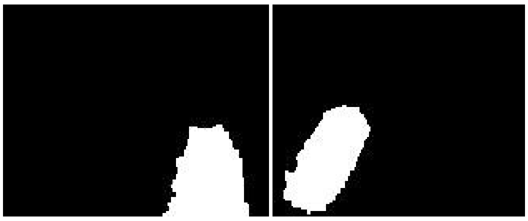

Fig 4(a&b): background subtracted frames

This back ground subtracted frames are also stored. Next level is the tacking and detection level

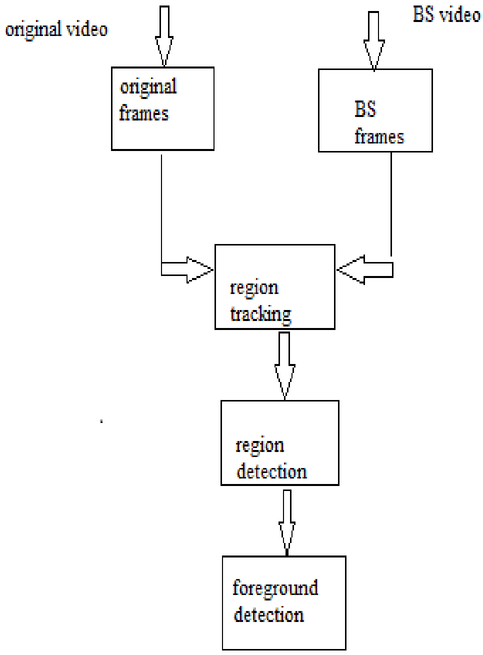

Fig 5: foreground detection process

The original image frames and subtracted image frames are taken as the inputs to detect the foreground and detection takes another process of tracking. Before tracking the binary image has been changed to the unsigned format to bring it back to original type. In tracking and detection it defines the whole frames and the system check for a region where it represents the largest component. In the subtracted frames it will track for the region =1 ie white areas and its maximum values are stored in variables x and y. The maximum and minimum values are defined and the condition checks the rows and columns and assign the area and this tracked area will be successfully detected and thus foreground object will be detected and all other area remains black ie assigned with zero. These detected frames are shown below:

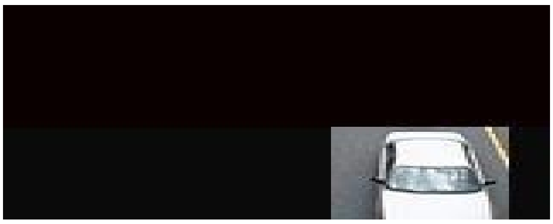

Fig 5(a): foreground detected frame 1

Fig 5(b): foreground detected frame 2

The detection can be done by subspace Gaussian model the recovery of original image with comparative good accuracy is done by means of this SGMM technique. The video sequence is detected to show foreground object and this detection may cause background to get subtracted.
Comparison between the image are done by means of parameters such as PSNR and MSE. For a video sequence it is splitted in to similar images the parameters remains same and they are calculated.
PSNR:it is the ratio of maximum of power signal to that of corrupted noise. For an image psnr can be calculated from mean square error[4].
MSE:Difference between estimator and estimated

$$MSE = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

Where I and K represent the image and noise respectively and m,n represents row and column respectively.

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\ &= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \end{aligned}$$

Consider the frames we can only get variations in PSNR and MSE values and this are mentioned below:

FRAMES	MSE	PSNR
4&6	0.0225	64.6430
2&8	0.0248	64.2126
10&15	0.0233	64.480

Table I: parameter analysis

V.CONCLUSION AND FUTURE WORK

The proposed system carried out adaptive and efficient means of background subtraction and it causes the system to be effective. So the background subtraction done was effective using SGMM. Some times may cause wrong clarification of error ie the static foreground may get incorporated to background and this can be overcome by saliency detection.
Saliency detection will reduce wrong clarifications and cause accurate detection of system with less error. PSNR and MSE can be comparatively studied in future work. High value of these parameter will be obtained for the second method.

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BIOGRAPHY

Aiswarya Muralidharan did her Bachelor of Technology in Electronics and communica tion at Amaljyothi college of Engineering ,kottayam ,kerala and pursuing her Master of Engineering in Communication system at Sri Shakthi Institute of Engineering and Technol ogy,Coimbatore,Tamilnadu.She has presente d one paper in International Conference and one paper in National Conference and published a journal.

S.Sivakumar completed his Master of Engineering in Communication System and presently working as Assistant professor in Sri Shakthi Institute of Engineering and Technology,Coimbatore and has four and half years of experience His area of interest is Antenna design. He published three journals

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