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A review paper on Background Extraction

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Abstract— This paper studies reviews of background extraction techniques. Object detection is most important step in video analysis. There are various background subtraction techniques for detecting the objects in video sequences. In a visual surveillance system dynamic scene due to fast illumination changes. There are various background subtraction algorithms available for determination of moving object in a scene, but many of them fail with dynamic background, noise, camouflage, camera shake, moved object, bootstrapping, shadows and illumination changes.

Index Terms— Background subtraction, Object detection, visual surveillance system, dynamic background, noise, camouflage, camera shake, moved object, bootstrapping, shadows, illumination changes.

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1 INTRODUCTION

Foreground extraction is the name of background extraction. This technique used in the fields of image processing and computer vision where in a detected image used for further processing. Background extraction generally used for number of applications in diverse disciplines, traffic monitoring, visual tracking and surveillance. After image preprocessing object localization is the next step which may make use of background extraction techniques. For detecting moving objects in video scene from static cameras, background extraction is widely used approach. Moving objects in the video frame considered as 'interest' and remaining part can be ignored. In such case region of interest (ROI) defined as foreground and remaining part of video frame as background. Moving objects in the video can be identified by taking difference between the current frame and the model referred as reference frame, often called "background image", or "background model".

There are three important issues which requires in majority of applications. First, robust against illumination changes and avoid detecting shadows of moving object. Second, detect moving object in case of complicated background, e.g. shimmering waves, swaying trees, camera jitters, fountains and rain, snows or smoke filled environments.

Recently, in image processing and computer vision new challenge has emerged, Digital video has become majority in our everyday lives. Examples of these hospitals, cutting edge system, airports, automated teller machine (ATM) and banking sites, courts, casinos, classrooms, retails stores, parking lots and elevators, for caring kids or seniors installed indoors as well as for traffic violation along road sides.

2 LITERATURE REVIEW

R.H. Evangelio [1] presents splitting Gaussians in mixture model (SGMM) for background extraction. Gaussian mixture models extensively used in the domain of surveillance. Due to low memory requirement this model used in the real time application. Split and merge algorithm provides the solution if main mode stretches and that causes weaker distribution problem. SGMM define criteria of selection of modes for the case of background subtraction. SGMM provides better background models in terms of low processing time and low memory requirements; therefore it is appealing in surveillance domain.

L. Maddalena and A. Pestrosino present Self Organizing Background subtraction (SOBS) [2] for detection of moving object based on neural background model. Such model generate self-organizing model automatically without prior knowledge about involved pattern. This adaptive model background extraction with scene containing gradual illumination variation, moving backgrounds and camouflage can include into moving object with background model shadows cast and achieves detection of different types of video taken by stationary camera. The introduction of spatial coherence into the background model update procedures leads to the so-called SC-SOBS algorithm that gives further robustness against false detection. L. Maddalena and A. Pestrosino discuss extensive experimental results of SOBS and SC-SOBS based on change detection challenges.

A. Morde, X. Ma, S. Guler [3] discusses background model for change detection. Change detection or foreground and background segmentation, has been extensively used in image processing and computer vision, as it is fundamental step for extracting motion information from video frames.

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Chybyshev probability inequality based background model present a robust real time background/foreground segmentation technique. Such model supported with peripheral and recurrent motion detectors. The system uses detection of moving object shadows, and feedback from higher level object tracking and object classification to refine the further segmentation accuracy. In this method present experimental result on wide range of test videos demonstrate the presented method with high performance with camera jitter, dynamic backgrounds, and thermal video as well as cast shadows.

Pixel based adaptive segmenter (PBAS) is one of the technique for detecting moving object in the video frame using background segmentation with feedback [4]. Martin Hofmann, Philipp Tiefenbacher and Gerhard Rigoll discuss the novel method for detection of object i.e for foreground segmentation. This adaptive segmentation technique follows a nonparametric background modeling paradigm and the background is designed by recently observed pixel history. The dicision threshold plays an important in pixel based adaptive segmentation for taking foreground decision. In this method learning model used to update background of the object. The learning parameter introduces dynamic controllers for each of dynamic per pixel state variables. Pixel based adaptive segmenter is state of the art methods.

Dirichlet process Gaussian mixture model is probabilistic model which assumes that all data points generated from a mixture of a finite number of Gaussian distribution having unknown parameter. There are different classes to execute a gaussian mixture model which corresponds to different strategies [5]. Dirichlet process is a probability distribution whose domain is a set of probability distribution. This process used in Baysian inference to describe prior knowledge about distribution of random variables, according to this formulation random variables are distributed based on one or another particular distribution.

3 Background Subtraction Techniques

Background subtraction technique has different algorithm, most of these techniques share common denominator: based on assumption that current video sequence I and static background B in front of which moving objects are observed. Along with the assumption each and every moving object made of different color (color distribution) from observed in B. Numerous background subtraction methods are summarized by the following formula:

$$\mathcal{X}_t(s) = \begin{cases} 1 & \text{if } d(\boldsymbol{I}_{s,t}, \boldsymbol{B}_s) > \tau \\ 0 & \text{otherwise,} \end{cases}$$

T is threshold, X_t is motion label at time t, d is difference between $I_{s,t}$, the color at time t and pixel s, and B_s, the background model at pixel s. The key point between several background extraction methods is how B is modeled and which distance metric d they use. In the following subsection, various background subtraction techniques are discussed as well as measure their respective distance.

A. Basic motion detection (Basic)

The background B is easily model through a single grayscale/color image void of moving objects. This image taken in absence of motion or estimated through a temporal median filter. With illumination changes and background modifications, it can be updated as follows:

$$\boldsymbol{B}_{s,t+1} = (1-\alpha)\boldsymbol{B}_{s,t} + \alpha.\boldsymbol{I}_{s,t}$$

Where α is a constant whose value ranges between 0 and 1. In simple background Model, pixels corresponding to foreground moving objects and pixel corresponding to background field can be detected by thresholding, any of those distance function,

$$\begin{aligned} d_0 &= |I_{s,t} - B_{s,t}| \\ d_1 &= |I^R_{s,t} - B^R_{s,t}| + |I^G_{s,t} - B^G_{s,t}| + |I^B_{s,t} - B^B_{s,t}| \\ d_2 &= (I^R_{s,t} - B^R_{s,t})^2 + (I^G_{s,t} - B^G_{s,t})^2 \\ &\quad + (I^B_{s,t} - B^B_{s,t})^2 \\ d_\infty &= \max\{|I^R_{s,t} - B^R_{s,t}|, |I^G_{s,t} - B^G_{s,t}|, \\ &\quad |I^B_{s,t} - B^B_{s,t}|\} \end{aligned}$$

Where R, G and B stand for the red, green and blue components and d_0 is a measure operating on grayscale images. Note that in this method use $I_t - 1$ is previous frame as background image B. Background detection configuration though motion changes becomes an inter-frame change detection process and intra-frame change detection process which are robust to illumination changes but suffers from a severe aperture problem since only parts of the moving objects are detected.

B. One Gaussian (1-G)

Modeling B with a single image requires a rigorously fixed background void of artifact and noise. Since this requirement cannot be satisfied in every real-life scenario, over a series of training frame many authors learned model probability density function (PDF) for each background pixel. In this case, the background subtraction problem becomes a PDF-thresholding issue for which high probability pixel is correspond to a background and a low probability pixel is likely to correspond to a foreground moving object.In this, the distance metric can be the following log likelihood:

$$d_G = \frac{1}{2}\log((2\pi)^3|\boldsymbol{\Sigma}_{s,t}|) + \frac{1}{2}(\boldsymbol{I}_{s,t} - \boldsymbol{\mu}_{s,t})\boldsymbol{\Sigma}_{s,t}^{-1}(\boldsymbol{I}_{s,t} - \boldsymbol{\mu}_{s,t})^T$$

or a Mahalanobis distance:

$$d_M = |\boldsymbol{I}_{s,t} - \boldsymbol{\mu}_{s,t}|\boldsymbol{\Sigma}_{s,t}^{-1}|\boldsymbol{I}_{s,t} - \boldsymbol{\mu}_{s,t}|^T.$$

Since the noisy area contains large covariance matrix value and for more stable areas its value is low, makes the threshold locally dependent on the amount of noise. In other words, the noisier a pixel is, the larger the temporal gradient $|I_{s,t} - \mu_{s,t}|$ has to be to get the pixel labeled in motion. This method is more flexible than the basic motion detection method. Since the mean and covariance of each pixel and illumination often changes in time, can also be iteratively updated in following this procedure:

$$\boldsymbol{\mu}_{s,t+1} = (1-\alpha).\boldsymbol{\mu}_{s,t} + \alpha.\boldsymbol{I}_{s,t}$$

$$\boldsymbol{\Sigma}_{s,t+1} = (1-\alpha).\boldsymbol{\Sigma}_{s,t} + \alpha.(\boldsymbol{I}_{s,t} - \boldsymbol{\mu}_{s,t})(\boldsymbol{I}_{s,t} - \boldsymbol{\mu}_{s,t})^T.$$

C. Gaussian Mixture Model (GMM)

Multimodal PDFs used some authors for backgrounds made of animated textures (such as trees waving by the wind or waves on the water). With K Gaussians mixtures models every pixel. Based on this method, a color at a given pixel s has probability of occurrence is given by:

$$P(\boldsymbol{I}_{s,t}) = \sum_{i=1}^{K} \omega_{i,s,t}.\mathcal{N}(\boldsymbol{\mu}_{i,s,t}, \boldsymbol{\Sigma}_{i,s,t})$$

where N is the ith Gaussian model and the diagonal covariance matrix is to be assumed, In this method, matched component parameters are updated as follows :

$$\omega_{i,s,t} = (1-\alpha)\omega_{i,s,t-1} + \alpha$$

$$\mu_{i,s,t} = (1-\rho).\mu_{i,s,t-1} + \rho.\boldsymbol{I}_{s,t}$$

$$\sigma^2_{i,s,t} = (1-\rho).\sigma^2_{i,s,t-1} + \rho.d_2(\boldsymbol{I}_{s,t}, \boldsymbol{\mu}_{i,s,t})$$

D. Codebook (CBRGB)

Another approach for background subtraction whose goal is to subtract with multimodal backgrounds is the so-called codebook method. In a training sequence, the method assigns to each background pixel a series of key color values which is stored in a codebook. Those codeword's defined which color a pixel is likely to take over a certain time period. For instance, a pixel in a stable area may be summarized by only one codeword whereas a pixel located over a tree shaken by the wind could be, for example, summarized by three values: green for the foliage, blue for the sky, and brown for the bark. With the assumption that shadows correspond to brightness shifts and real foreground moving objects to chroma shifts, the original version of the method has been designed to eliminate false positives caused by illumination changes. This is done by performing a separate evaluation of color distortion:

$$\sqrt{I_{s,t}^{R^2} + I_{s,t}^{G^2} + I_{s,t}^{B^2} - \frac{(\mu_{i,s}^R.I_{s,t}^R + \mu_{i,s}^G.I_{s,t}^G + \mu_{i,s}^B.I_{s,t}^B)^2}{\mu_{i,s}^{R^2} + \mu_{i,s}^{G^2} + \mu_{i,s}^{B^2}}} < \tau$$

and brightness distortion:

$$\alpha_{i,s} \le I_{s,t}^{R^2} + I_{s,t}^{G^2} + I_{s,t}^{B^2} \le \beta_{i,s}$$

E. Eigen Backgrounds (Eigen)

A non pixel-level method has been proposed by Oliver discussed background model by eigen space concept. The important element of this method is that the ability of learning the background model from unconstraint video sequences, even when they contain dynamic background and moving foreground objects. While pixel-level statistics used in previous approaches, Eigen takes into account neighboring statistics. Thus it has a more ideal definition on background which, hopefully, makes it more robust to dynamic backgrounds.

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4 CONCLUSION

Detection of moving object has widely been adopted by the, traffic monitoring, human-action recognition, human-computer interaction, object tracing and industry or organization because of its broad applicability in real life and this has been growing more and more. There are many existing methods for background subtraction all having some merits and demerits. In this paper different methods for background subtraction have been discussed on the basis of there advantages and disadvantages. But still more work require to improve accuracy.

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