Video Change Detection System Using Multimode Background Subtraction

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Abstract: In this paper, we are implementing the multimode background subtraction Background subtraction a pre-processing step in video processing and therefore have numerous applications including video surveillance, traffic monitoring, human detection, gesture recognition, etc. The device mechanisms are background modeling, model update, pixel category, and the usage of multiple shade areas. The machine first creates multiple background models of the scene accompanied with the aid of initial foreground/background probability estimation for every pixel. Next, the image pixels are merged collectively to shape megapixels, which are used to spatially denoise the initial probability estimates to generate binary mask for both RGB and YCbCr color spaces. The masks generated after processing these input images are then combined to separate foreground pixels from the background.

Keywords: Computer vision, change detection, background model bank, background subtraction, color spaces, Discrete Wavelet Transform, binary classifiers, foreground segmentation, pixel classification.

INTRODUCTION

Video change detection or Background Subtraction (BS) is one of the most widely studied topics in computer vision. It is a initial step in video processing and it was useful in many real time applications like video surveillance, traffic monitoring, human detection, object tracking and object counting. The background subtraction (BS) process gives a foreground (FG) binary mask of the given input image and a background. Background subtraction is a difficult problem because of the diversity in background scenes and the changes originated from the camera itself. Two main problems to background subtraction are change detection and salient motion detection. Change detection addresses the detection of the changes between two images. So, background subtraction is a particular case when one image is the background image and the other one is the current image, and the changes are due to moving objects. Considering, salient motion detection aims to find semantic regions and to filter out the unimportant areas.

BS is a difficult problem because of the diversity in background scenes and the changes originated from the camera itself. Scene variations can be in many forms such as, to name just a few, dynamic background, illumination changes, intermittent object motion, shadows, highlights, camouflage as well as a multitude of environmental conditions like rain, snow, and change in sunlight [1].

Multimode Background Subtraction (MBS) with following major innovations: Background Model Bank (BMB), model update mechanism, MP-based spatial denoising of pixel-based probability estimates, fusion of multiple binary masks, and use of multiple color spaces for BS process.

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 socalled 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. 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.

PROPOSED WORK

Background Subtraction can be summarized as a five-step process: pre-processing, background modelling, foreground detection, data validation and model update. Pre-processing involves simple image processing on input video such as format conversion and image resizing for subsequent steps. Background modelling is responsible for constructing a statistical model of the scene, followed by pixel classification in the foreground detection step. In the data validation step, falsely-detected foreground pixels are removed to form the final foreground mask [6]. The final step is to update the model if necessary.

A. Color spaces for Background Subtraction:

RGB is a popular choice for a number of reasons: (a) the brightness and color information are equally distributed in all three color channels; (b) it is robust against both environmental and camera noise [7]; (c) it is the output format of most cameras and its direct usage in BS avoids the computation cost of color conversion [8]. YCbCr is the least sensitive to noise, shadow and illumination changes. During intermediate lighting conditions, both RGB and YCbCr color spaces complement each other in providing a robust FG/BG classification.

B. Background Modelling:

Most BG models use a variant of multi-modal pixel-wise statistical background model. Such an approach has two problems: first, it is difficult to determine the correct number of modes for modelling the pixel probability distribution function. Second, and more importantly, inter-pixel dependencies are overlooked, which leads to poor segmentation results. This initial set of BG models is then merged together into a number of average BG models using an iterative sequential clustering procedure. Two BG mean models (p and q in vector form) with correlation measure greater than the pre-defined parameter corr_th are merged and replaced by their average. The correlation measure is defined as

$$Corr\ (p,q) = \left(\frac{(p-\mu_p)(q-\mu_q)^l}{\sqrt{(p-\mu_p)(p-\mu_p)^l}\sqrt{(q-\mu_q)(q-\mu_q)^l}} \right)$$

where μ_p and μ_q are defined as:

$$\mu_p = \frac{1}{|X|}\sum_j pj \ and \ \mu_q = \frac{1}{|X|}\sum_j qj$$

The use of multiple BG models allows us to capture scene more accurately while keeping spatial dependencies intact. Another advantage of BMB is that it is computationally simpler than other multi-mode approaches – as we will demonstrate, we choose a model at frame level and ignore the rest of the BG models in the BMB.

C. Binary Classification:

It is a four step process: color channel activation/deactivation, pixel-level probability estimation, MP formation and average probability estimation.

1. *Color-Channels Activation/Deactivation:* This step is responsible to activate/deactivate the color channels Cb and Cr. Both color channels are used if the mean intensity of input image is greater than empirically determined parameter channel_th, which otherwise are not employed.
2. *Pixel-Level Probability Estimation:* Pixel-wise error, *err*_D (X) is calculated between each color channel from both RGB and YCbCr spaces and the chosen BG model as follows.
$$err_D(X) = |I_D(X) - \mu D_n(X)|$$
Where D denotes the color channel in question, I_D (X) is the input image, and μ D_n(X) is the chosen average BG model. Once we have calculated the error for each individual pixel, we estimate an initial probability i *p* for each pixel by passing them through a sigmoid function.
$$ip\big(err_D(X)\big) = \frac{1}{(1+e^{-err_D(X)})}$$
3. *Mega-Pixel Formation:* In the superpixel segmentation using slic algorithm we have to give the number of blocks which is static but as extension we incorporate adaptive block number selection approach for better analysis. To perform adaptive block size determination we are using wavelet transform. The wavelet type is haar. The discrete wavelet transforms (DWT) of the preprocessed image I is computed as follows:
$$[I_{Ap}, I_{Ho}, I_{Vr}, I_{Dg}] = DWT(I) \qquad (1)$$
Here, I_{Ap} captures the approximation coefficients of the image, whereas $[I_{Ho}, I_{Vr}, I_{Dg}]$ contain the detail coefficients in horizontal, vertical, and diagonal sub-bands respectively. The detail and approximation coefficients obtained using Eq. 1 represent the first level DWT coefficients. Another level of DWT is applied on the approximation band, I_{Ap}, as follows:
$$[I'_{Ap}, I'_{Ho}, I'_{Vr}, I'_{Dg}] = DWT(I_{Ap}) \qquad (2)$$
Here, I'_{Ap} and $[I'_{Ho}, I'_{Vr}, I'_{Dg}]$ represent the second level DWT approximation and detail coefficients of input image *I* respectively. DWT is useful to enable multi-resolution

analysis of the given image. For better analysis we are using four level of DWT.

DBSCAN is a density based clustering algorithms in which clusters are defined as high density areas, whereas the sparse regions are treated as outliers or borders to separate clusters. Two SPs are merged together into a MP under the following criteria:

$$MP = \begin{cases} 1 & dist \leq colorthreshold \cap SPs\ are\ adjacent \\ 0 & dist > colorthreshold \cup SPs\ are\ non-adjacent \end{cases}$$

4. *Average Probability Estimation and Labelling:* The next step is to compute the average probability of a MP y, denoted as AP y, with a total of Y pixels:

$$AP_y = \frac{1}{Y}\sum_{np=1}^{Y} ip(np)$$

Where np is the pixel index and i p is the initial FG/BG probability estimate of each pixel.

D. Model Update:

Model update is an essential component of an algorithm to deal with scene changes that take place with the passage of time.

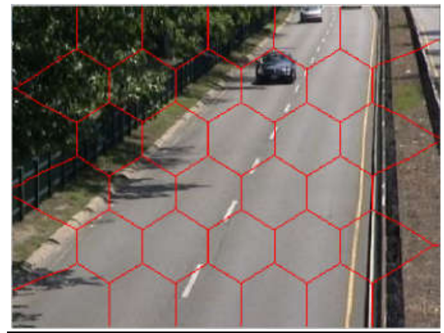
$$modelupdate = \begin{cases} 1 & if\ rate\ of\ change\ \geq th \\ 0 & otherwise \end{cases}$$

Where th is an empirically-determined parameter that signifies a significant enough change for model update. The rateOfChange is calculated based on the deviation of the number of FG pixels in current frame from the running mean.

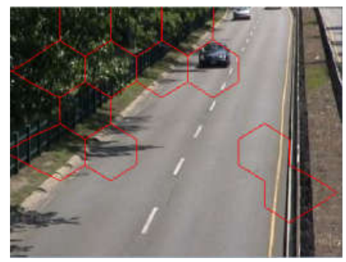
RESULTS

Input Image:

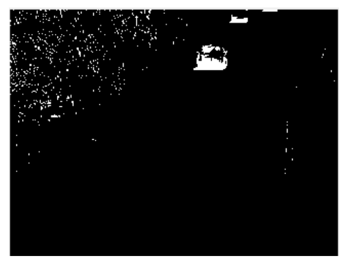
Super pixel (SP) segmentation:



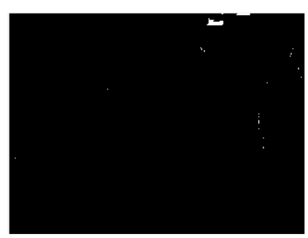
DBSCAN Clustering:



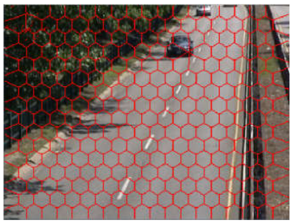
Binary Mask:



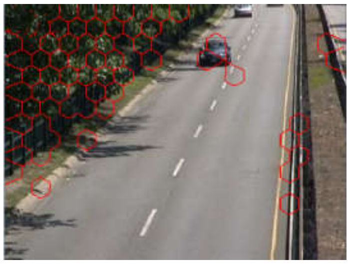
Binary Mask:



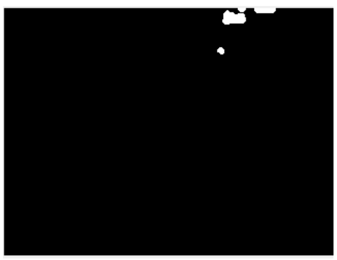
Mega Pixel (MP) Segmentation:



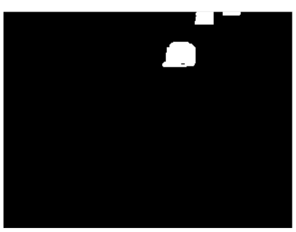
DBSCAN Clustering:



Final Segmented Result:



Ground truth:



Precision (PRE) =0.8299

Recall (RE) =0.2669

Specificity (sp) =0.0694

False Negative Rate (FNR) =0.0694

False Positive Rate (FPR) =0.9306

Percentage of Wrong Classifications (PWC) =0.4406

F-measure (Fm) =0.4040

CONCLUSION

In this paper a new approach is proposed for video change detection using universal multimode background segmentation using Background Model with color spaces RGB and YCbCr. Our approach has been also tested on dataset of complex background scenes. An accurate new method for detecting moving object is proposed, based on background subtraction. In the superpixel segmentation using slic algorithm we have to give the number of blocks which is static but as extension we incorporate adaptive block number selection approach for better analysis. The testing data is measured by evaluation metrics like precision, recall, specificity, False Negative Rate (FNR), False Positive Rate (FPR), Percentage of Wrong Classifications (PWC), F-measure (Fm).

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