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SURVEY ON BACKGROUND MODELING AND FOREGROUND DETECTION FOR REAL TIME VIDEO SURVEILLANCE

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Abstract

In Image Processing, a very trivial task is to detect the changes in the multiple images of the same scene of a real time instant. The task is not only trivial but also very indispensable as it brings into play a great number of diversified subject area applications such as, remote sensing, surveillance, medical diagnosis and treatment, security surveillance, and underwater sensing. The main perspective of this survey is to give a nomenclature study of the general processing steps and prime decision rules used in the advanced change detection algorithms, which are employed for the real time video surveillance. The real time video surveillance models encompass the predictive and the background modelling techniques. The survey also emphasizes on the comparison of the processing speed of the various change detection algorithms applied in real time video surveillance.

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Keywords: *Background subtraction, foreground detection, background modeling, ViBe, SOBS, PBAS.*

1. Introduction

A detailed understanding of video sequences is an active research in the current era. Many applications in this research arena (surveillance of videos, capturing optical motion, multimedia application) initially needs to find the moving objects in the picture. Foreground: detachment of moving object from the static information background is the basic operation needed. According to[1,2,3] then main process used is the background subtraction and recent surveys can be found. Acquiring a background image which does not include any moving object is the most elementary way to model to the background. In some cases, background is not usable, under critical situation can always be changed[4] the background like illumination changes, objects being introduced or picture taken from far

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away from the distance. Thus, the background representation model must be more robust and adaptive. Change detection[5,6] and Salient motion detection[7] are two closely related issues to background subtraction. The modifications between two frames address the detection of the background. Thus the special case background subtraction is nothing but, an image with background image, current image and the dynamic background change. On the other hand, finding semantic regions and filter out the unimportant areas are the goals of salient motion detection. The human optic system is derived to the idea of saliency detection, where the foremost phase of human visual modality is a flying and simple pre-attentive operation. So, a peculiar example of background detection is salient motion detection.

In surveillance system, Dynamic background and illumination changes are challenging task and the main difficulties are: Dynamic backgrounds: its present four typical examples are: Camera jitter, waving trees, water rippling and water surface. In these cases, foreground mask by a mixture of Gaussian used. But there is a great measure of false detection may take place.

Illumination changes: it appears either gradual or sudden light changes. Gradual changes in climate that handled by MOG with big false detection for detection foreground mask. Sudden alterations of light on/off every pixel can be impressed by these varieties which also generate false detection.

2. Literature Survey

Various survey of background subtraction can be found in literature, only none of them address an overall review in this area. In 2000, Mc Ivor models of nine algorithms first compare in this survey, are confined to describe the analysis of algorithms. In 2004, Piccardi gave a reassessment on seven methods and a detailed classification based on velocity, retention requirements and region accuracy. This review enables readers to do a comprehensive study about the complexity of the different methods and can effectively assist them to select the most adapted methods for a specific application. In 2005, Cheung and Kamath[8] categorized several techniques into non-recursive and recursive.

Sticking to this categorization, Elhabian et al.[9] gave a detailed review in background modeling. Entirely the same to the context, non-recursive and recursive techniques are adapted for background maintenance scheme, compared with background modeling . In 2010, Cristani et al.[10] reviewed the well known algorithms classifying them in single monocular sensor or multi-sensing elements, but this classification is not optimal in the sensory faculty that some methods can be in the two categories. In 2010, Bouwmans et al. gave a brief review on statistical background modeling methods to detect foreground based on statistical models.

2.1 Background modeling methods

The Mixture of Gaussian method by H. Wang based background model is the most common approach. Bouwmans et al.[11] provided a sight and an original classification of the numerous improvements of the original MOG.

R.Amali et al.[12] developed a method called Rapid Background Subtraction, By using sample based background subtraction. This algorithm generated by combining three techniques. First technique, initially this method takes first two consecutive frame has a background model after particular threshold period background model can be updated. Next technique is classification of pixel correspondence to background pixel model and also shadow detection method. Finally updating of background pixel model can be updated by random pixel locations. By this method accuracy and efficiency can be increased this method also derived from ViBe.

Subspace learning methods have been applied to model the background in the approximation to represent online data content while reducing dimension significantly. The first method using Principal Component Analysis (PCA) was suggested by Oliver et al. Bouwmans[13] provided a sight and an original classification of these advances. Furthermore, it gave a comparative rating of the stochastic variables and evaluate them with (SG, MOG, and KDE) the state-of-art algorithms by using the Wallflower dataset. Critical situations met in video surveillance generate imprecision and uncertainties in the whole process of background subtraction. Thus, some authors have recently introduced fuzzy concepts in the different steps of background subtraction.

Robust Principal Components Analysis (RPCA) models have been recently developed in the literature. Recently, Bouwmans and Zahzah initiated a comprehensive review of RPCA-PCP based methods for testing and ranking existing algorithms for foreground detection.

2.2 Foreground detection methods

For foreground detection which is a focal task in image processing numerous methods are already available but, they mostly concentrate only on stored videos and images. Only a handful of methods are available for real time foreground detection, few enticing ones among them are Self-Organizing Background Subtraction[14], Pixel Based Adaptive Segmenter [15] and Visual Background extractor methods[16]. These three methods have helped to spur a lot of other enhanced methods for the purpose of background detection.

Self-Organizing Background Subtraction (SOBS) algorithm accurately handles scenes containing moving backgrounds, gradual illumination variations, and shadows cast by moving objects, and is robust against false detections for different types of pictures taken with stationary cameras. Even without prior knowledge self-organizing method can detect the moving object based on background model.

The neural network based image sequence model, models itself by learning in a self-organizing manner. The variations in the image sequence are viewed as trajectories of pixels along the time domain. The neural network exhibits a competitive win at all times function, this winner-take function is in turn coupled with the local synaptic plasticity behaviour of the neurons. The learning process of the active neurons is seen to be spatially restricted which is founded on their local neighbourhood. The neural background model can be portrayed as an adaptive one, since it adapts well to changes in the scene and succeeds in capturing most of the prominent change of features in the image sequence.

Pixel Based Adaptive Segmenter (PBAS) is a model which holds the recently observed pixel values and deigns the background. PBAS model contains a set of divisions. The decision block which is the prime component makes a decision either for or against the foreground biased on the per-pixel threshold of the current image and as well the background. Adding on to the designing process of the background model, the model gets updated over time with a defined procedure to carry out the changes in the background.

The per-pixel learning parameter is the one which governs this update. The centroid of innovative fact in the PBAS approach is paved by the two per-pixel threshold which changes the background dynamics. Seemingly, the choice of the foreground decision is made from the foreground threshold value. The foreground decision depends on a decision threshold. Due to these enthralling differences the PBAS outshines almost all the state-of-the-art approaches.

ViBe works on random selection which leads to a smooth exponential decaying lifespan given a sample set which comprises the pixel models. The other novelty of the approach is pitched upon the post-processing which gives spatial consistency with the aid of a faster spatial information propagation technique.

The pixel values are distributed in a random order among the neighboring pixels. The other descendent of the novelty in the approach credits from the background initialization done instantaneously. Hence the algorithm can proceed from the progressive second frame. ViBe sums up to a satisfactory outcome in most of the scenarios but when it comes to scenarios with darker or shadowy backdrop it gets intriguing.

The performance of the ViBe[17] method happens to seemingly increase when convoyed with other distance measure rather than the ancestral Euclidean (L2) distance measure. The performance increase has been measured based on the reduction in the computation time for processing the image.

A novelty of real-time hardware implementation[18] of the ViBe (Visual Background Extractor) background generation algorithm in the reconfigurable FPGA device. This novel method combines the advantages of typical recursive and non-recursive approaches and achieves very good foreground object segmentation results. In this work the issue of porting ViBe to an FPGA hardware platform is discussed, two changes to the original approach are proposed and a detailed description of the implemented system is given.

Generally, FPGA has been experimented with the following methods: the first one uses a Mixture of Gaussian with input as HD grey scale video stream processing and the frame specification is 1920 × 1080 @ 20 fps; the second method is Horparsert method where the frame specification is 1024 × 1024 with a capturing speed of 32.8 fps for video stream processing and a high level synthesis language Impulse-C has been partially applied in this method; the third method is Codebook with a frame specification of 768 × 576 with a capturing speed of 60 fps for video stream processing, Clustering has been applied in this method for HD, color video stream processing.

An FPGA implementation of background generation algorithms can be used in hardware accelerators, besides this method has been applied to implement server video surveillance system.

3. COMPARATIVE ANALYSIS

Pixel based adaptive segmenter from result of figure(1) big false positive rate to reduce them perform median filter to capture sharp pictures. The processing of frames is around 180 frames per second where each frame sizes up to 640x480 pixels. In this method to generate exact results by both the operation so computation time can be increased. But this method suit for dynamic background and illumination changes.

Figure 1: (a) Original image, (b) Result of Pixel based adaptive segmenter method

(a) *(b)*

The Self-Organizing Background Subtraction (SOBS) algorithm deploy the technique for moving object detection based on the neural background model automatically generated by a self-organizing method, without prior information about the policy involved. The processing of frames is around 200 frames per second where each frame sizes up to 640x480 pixels. But false detection is low that is shown if figure(2) compare to other real time surveillance system.

Figure 2: (a) Original image, (b) Result of Self-Organizing Background Subtraction method

(a) *(b)*

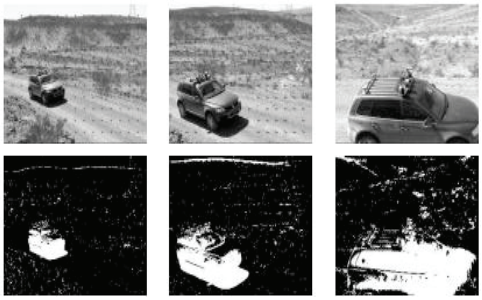
ViBe (Visual Background extractor)[19] figure(3) deploys random selection policy providing a smooth exponential decaying lifespan for any sample set. The main posits of the approach include the post-processing, a faster spatial information propagation, instantaneous background initialization enabling the algorithm with the second sequential frame as input.

This ViBe approach is universally applicable to a diversified environment and has proved to be outsourcer for springing up several other new approaches. As mentioned earlier, the outcome of ViBe is quiet satisfactory for almost all background, but gets challenging for certain scenarios with darker background aspects alone in terms of detection. The processing of frames is around 250 frames per second where each frame sizes up to 640x480 pixels [20]

Figure 3: (a) Original image, (b) Result of Visual Background Extractor method

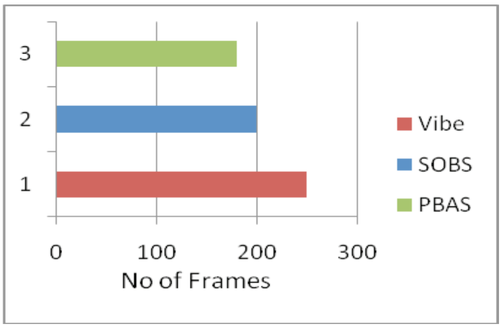
(a)

(b)



Comparative analysis of ViBe, SOBS and PBAS methods based on the number of processed frames per second.

Figure 4: Comparison between ViBe, SOBS, PBAS based on processed frames per second



From figure(4) shows that chart short time and number of frames can be processed by Vibe[20] method is comparatively less then to other real time surveillance systems. It also called a universal method because it works all situations, illuminations.

4. CONCLUSION

A far-reaching survey of real time background subtraction models applied on image backgrounds has been summarized. It embodies two important aspects making it different and striking with respect to the other reviews. Foremost, it considers a classification of the background models based on the mathematical instruments employed. Second, compares the processing speed with real time methods. From this survey, a wrap up that Vibe method is more efficient and many frames can be processed per second is clear. Besides, numerous methods can be used or derived from this method. Intriguing area for this method is a darker background, which can be handled in a better way if prior pre processing is carried out. Similarly, shadowy background is also another successive challenge for ViBe, which can be vapourized by proper post processing steps. From this overall performance of ViBe is more efficient and also processing speed is very high by using this in real time systems.

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