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Comparative Study of Different Approaches for Foreground Background Subtraction from Video Clips: A Review

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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.

KEYWORDS: Foreground Detection, Background Subtraction, Surveillance Video, Modelling

I 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, and multi-media 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 reference 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 changed4 the background like illumination changes, objects being introduced or picture taken from far away from the distance. Thus, the background representation model must be more robust and adaptive. Change detection and Salient motion detection 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.

II LITERATURE SURVEY

In 2016 IEEE transactions on circuits and systems for video technology Jiamming Guo et al. [7] presented an article. In this presented article, extracting an object of interest from a single video still faces significant difficulties when the object has variegated appearance, manifests articulated motion, or experiences occlusions by other objects. In this paper, we present a video co-segmentation method to address the aforementioned challenges. Departing from the object ness attributes and motion coherence used by traditional foreground-background separation and video segmentation methods, we place central importance in the role of "common fate". Specifically, the different parts of the object should persist together in all the videos despite the possible presence of incoherent (e.g. articulated) motions. To accomplish this idea, we first extract seed super pixels by a motion-based foreground segmentation method. We next formulate a set of initial to-link constraints between these super pixels based on whether they exhibit the characteristics of common fate or not. An iterative manifold ranking algorithm is then proposed to trim away the incorrect and accidental linkage relationships. Having discovered the parts that should cohere together, we next perform clustering to extract the entire object and to handle the case where there might be multiple objects present. This clustering is performed at two levels: the super pixel-level and the object level. This two-level clustering algorithm also performs automatic model selection to estimate the number of object classes extracted.

Finally, a multiclass labeling Markov random field is used to obtain a refined segmentation result. To evaluate the performance of our framework, we introduce a new dataset in which the videos have complex form and motion which are liable to ambiguity in interpretation. Our experimental results on this dataset show that our method successfully addresses the challenges in the extraction of complex objects and outperforms the state-of-the-art video segmentation and co-segmentation methods in our dataset.

In 2016 IEEE Jiun-Yu Kao et al. [8] proposed a paper. In this paper proposed, moving object segmentation in video has uses in many applications and is a particularly challenging task when the video is acquired by a moving camera. Typical approaches that rely on principal component analysis (PCA) tend to extract scattered sparse components of the moving objects and generally fail in extracting dense object segmentations. In this paper, a novel label propagation framework based on motion vanishing point (MVP) analysis is proposed to address the challenges. A weighted graph is constructed with image pixels as nodes and the MVP-guided approach is used to define the graph weights. Label propagation is then performed by incorporating the graph Laplacian. In addition, a PCA result is used to initialize the foreground/background labels. Experiments on the Hopkins data set of outdoor sequences captured by a hand-held moving camera demonstrate that the proposed label propagation method outperforms state-of-the-art PCA and spectral clustering methods for a dense segmentation task. Moreover, the framework is capable of correcting mislabeled foreground pixels and thus does not require accurate initial label assignment.

In 2015 IEEE transaction on circuits and systems for video technology Xinchen Ye et al. [9] proposed an article. In this article proposed, Separation of video clips into foreground and background components is a useful and important technique, making recognition, classification, and scene analysis more efficient. In this paper, we propose a motion-assisted matrix restoration (MAMR) model for foreground–background separation in video clips. In the proposed MAMR model, the backgrounds across frames are modeled by a low-rank matrix, while the foreground objects are modeled by a sparse matrix. To facilitate efficient foreground–background separation, a dense motion field is estimated for each frame, and mapped into a weighting matrix which indicates the likelihood that each pixel belongs to the background. Anchor frames are selected in the dense motion estimation to overcome the difficulty of detecting slowly moving objects and camouflages. In addition, we extend our model to a robust MAMR model against noise for practical applications. Evaluations on challenging datasets demonstrate that our method outperforms many other state-of-the-art methods, and is versatile for a wide range of surveillance videos.

In 2015 IEEE transaction on image processing Yu-Gang Jiang et al. [10] presented an article. In this presented article, "Human action recognition in unconstrained videos is a challenging problem with many applications. Most state-of-the-art approaches adopted the well-known bag-of features representations, generated based on isolated local patches or patch trajectories, where motion patterns, such as object–object and object-background relationships are mostly discarded. In this paper, we propose a simple representation aiming at modeling these motion relationships. We adopt global and local reference points to explicitly characterize motion information, so that the final representation is more robust to camera movements, which widely exist in unconstrained videos. Our approach operates on the top of visual code-words generated on dense local patch trajectories, and therefore, does not require foreground–background separation, which is normally a critical and difficult step in modeling object relationships. Through an extensive set of experimental evaluations, we show that the proposed representation produces a very competitive performance on several challenging benchmark data sets. Further combining it with the standard bag-of-features or Fisher vector representations can lead to substantial improvements.

In 2011 IEEE transaction, Shih-Chia Huang et al. [11] proposed that the, Motion detection is the first essential process in the extraction of information regarding moving objects and makes use of stabilization in functional areas, such as tracking, classification, recognition, and so on. In this paper, we propose a novel and accurate approach to motion detection for the automatic video surveillance system. Our method achieves complete detection of moving objects by involving three significant proposed modules: a background modeling (BM) module, an alarm trigger (AT) module, and an object extraction (OE) module. For our proposed BM module, a unique two-phase background matching procedure is performed using rapid matching followed by accurate matching in order to produce optimum background pixels for the background model. Next, our proposed AT module eliminates the unnecessary examination of the entire background region, allowing the subsequent OE module to only process blocks containing moving objects. Finally, the OE module forms the binary object detection mask in order to achieve highly complete detection of moving objects. The detection results produced by our proposed (PRO) method were both qualitatively and quantitatively analyzed through visual inspection and for accuracy, along with comparisons to the results produced by other state of-the-art methods. The analyses show that our PRO method has a substantially higher degree of efficacy, outperforming other methods by an *F*1 metric accuracy rate of up to 53.43%.

S. No.	Author	Title	Method	Contribution	Parameter	Year	Publication
1	Jiaming Guo et al.	Video Foreground Co-Segmentation Based on Common Fate	Co-Segmentation based Common Fate (Two Level Clustering)	Experimental results on this dataset show that our method successfully addresses the challenges in the extraction of complex objects and outperforms the state-of-the-art video segmentation and co-segmentation methods in our dataset.	$\alpha = 0.4$ $\beta = 0.3$ $\gamma = 0.98$ $\theta = 0.4$ $\sigma_c = 20$ $\sigma_p = 0.25$ $\eta = 0.75$ $\lambda = 0.1$ to 0.5	2016	IEEE
2	Kao et al.	Geometric-Guided Label Propagation For Moving Object Detection	PCA with MVP	Experiments on the Hopkins data set of outdoor sequences captured by a hand-held moving camera demonstrate that the proposed label propagation method outperforms state-of-the-art PCA and spectral clustering methods for a dense segmentation task. Moreover, the framework is capable of correcting mis-labeled foreground pixels and thus does not require accurate	$\alpha = 0.4$ $\beta = 0.3$ λ = Varied	2016	IEEE

				initial label assignment.			
3	**Xinchen Ye et al.**	Foreground Background Separation From Video Clips via Motion-Assisted Matrix Restoration	MAMR	This model to a robust MAMR model against noise for practical applications. Evaluations on challenging datasets demonstrate that our method outperforms many other state-of-the-art methods, and is versatile for a wide range of surveillance videos.	α = Varied $\beta = 0.3$ $\lambda = 10$ $\gamma = 1$ $\rho = 2$	2015	IEEE
4	**Yu-Gang Jiang et al.**	Human Action Recognition in Unconstrained Videos by Explicit Motion Modeling	Dense Trajectories	Proposed representation produces a very competitive performance on several challenging benchmark data sets. Further combining it with the standard bag-of-features or Fisher vector representations can lead to substantial improvements.	Accuracy = 88%	2015	IEEE
5	**Shih-Chia Huang et al.**	An Advanced Motion Detection Algorithm with Video Quality Analysis for Video Surveillance Systems	PRO Method	The detection results produced by our proposed (PRO) method were both qualitatively and quantitatively analyzed through visual inspection and for accuracy, along with comparisons to the results produced by other state of- the-art methods. The analyses show that our PRO method has a substantially higher degree of efficacy, outperforming other methods by an *F*1	Recall = 0.89 Precision = 0.82 F-Metric = 0.85	2011	IEEE

				metric accuracy rate of up to 53.43%.			

III BACKGROUND MODELLING METHOD

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 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.

IV 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 behavior of the neurons. The learning process of the active neurons is seen to be spatially restricted which is founded on their local neighborhood. 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.

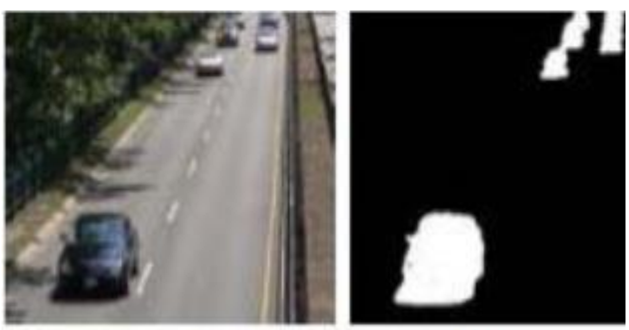
V COMPARATIVE ANALYSIS

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.

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.

(a) (b)

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



(a) (b)

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

VI 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 vaporized by proper post processing steps.

REFERENCES

1) A Mc Ivor, Background subtraction techniques, in: International Conference on Image and Vision Computing, New Zealand, IVCNZ 2000, November 2010.
2) M. Piccardi, Background subtraction techniques: a review, in: IEEE International Conference on Systems, Man and Cybernetics, October 2004.
3) T. Bouwmans, Recent advanced statistical background modeling for foreground detection: A systematic survey, Recent Patents Computer Science (2011).
4) T. Bouwmans, J. Gonzalez, C. Shan, M. Piccardi, L. Davis, Special issue on background modeling for foreground detection in real-world dynamic scenes, Mach. Vis. Appl. (2014).
5) H. Wang, D. Suter, A re-evaluation of Mixture-of-Gaussian background modeling, in: IEEE International Conference on Acoustics, Speech, and Signal Processing, ICASSP 2005, March 2005.
6) R. Radke, S. Andra, O. Al-Kofahi, B. Roysam, Image change detection algorithms: a systematic survey, IEEE Transaction on Image Processing (2005).
7) Jiaming Guo, Loong-Fah Cheong, and Robby Tan, “Video Foreground Co-Segmentation Based on Common Fate”, IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY, 2016.
8) Jiun-Yu Kao, Dong Tian, Hassan Mansour, Anthony Vetro and Antonio Ortega, “Geometric-Guided Label Propagation For Moving Object Detection”, IEEE 2016.
9) Xinchen Ye, Jingyu Yang, Xin Sun, Kun Li, Chunping Hou, and Yao Wang, “Foreground–Background Separation from Video Clips via Motion-Assisted Matrix Restoration,” IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY, VOL. 25, NO. 11, NOVEMBER 2015.

10) Yu-Gang Jiang, Qi Dai, Wei Liu, Xiangyang Xue, and Chong-Wah Ngo, “Human Action Recognition in Unconstrained Videos by Explicit Motion Modeling”, IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 24, NO. 11, NOVEMBER 2015.
11) T. Bouwmans, F. El-Baf, B. Vachon, Background modeling using mixture of Gaussians for foreground detection: A survey, Recent Patents Computer Science (2008).
12) R.Amali Therese Jenif, C.Akila,Dr. V.Kavitha, ”Rapid Background Subtraction from video Sequence”,IEEE International conference on computing, Electronic and Electrical Technologies 2012.
13) Thierry Bouwmans, El Hadi Zahzah,” Robust PCA via Principal Component Pursuit: A review for a comparative evaluation in video surveillance” Elsevier Computer Vision and Image Understanding Volume 122, May 2014.
14) L. Maddalena, A. Petrosino, The SOBS algorithm: What are the limits? In: IEEE Workshop on Change Detection, CVPR 2012, and June 2012.
15) M. Hofmann, P. Tiefenbacher, G. Rigoll, Background segmentation with feedback: The pixel-based adaptive segmenter, in: IEEE Workshop on Change Detection, CVPR 2012, June 2012.
16) O. Barnich, M. Van Droogenbroeck, ViBe: a powerful random technique to estimate the background in video sequences, in: International Conference on Acoustics, Speech, and Signal Processing, ICASSP 2009.
17) PL St-Charles, GA Bilodeau,” Improving Background Subtraction using Local Binary Similarity Patterns” Applications of Computer Vision (WACV), 2014 IEEE Computer Society Winter Conference.
18) Tomasz Kryjak, Marek Gorgon,” Real-time Implementation of the ViBe Foreground Object Segmentation Algorithm”, Proceedings of the 2013 Federated Conference on Computer Science and Information Systems.
19) O. Barnichsz and M. Van Droogenbroeck, “Vibe: A universal background subtraction algorithm for video sequences,” Image Processing, IEEE Transactions 2011.