IPASJ International Journal of Information Technology (IIJIT)
Web Site: http://www.ipasj.org/IIJIT/IIJIT.htm
A Publisher for Research Motivation ....
Email:editoriijit@ipasj.org
Volume 6, Issue 5, May 2018
ISSN 2321-5976

Foreground detection algorithms: A survey

Kritika Singh[1], Vishal Gupta[2]

[1] Ambedkar Institute of Advanced Communication Technologies and Research, Department of Computer Science & Engineering, New Delhi, India

[2]Ambedkar Institute of Advanced Communication Technologies and Research, Department of Computer Science & Engineering, New Delhi, India

ABSTRACT

The task of identifying foreground from a picture or a video is a big challenge in many computer-vision applications. Foreground detection is useful in the security surveillance systems especially in the crowded areas such as parking lots, train stations, airports, movie theaters, hospitals and other mass gatherings. The basic concept to model any background consists of capturing a background image which does not have any moving object in it. However, in many cases, the background does not remain stationary, it may change in the form of illumination changes, tree leaves waving etc. Thus, it is essential to acquire a background model which is not only robust but is also adaptive to background changes. The objective of this paper is to provide a survey of various approaches found in the foreground detection field. The paper concludes by highlighting the advantages and the limitations of these approaches.

Keywords: Foreground detection, Background subtraction, Background modeling, Mixture of Gaussians.

1. Introduction

The most prominent or visibly large region in any picture or a video is known as the foreground object. In contrast to the background, the portion that is much closer to the viewer can be defined as the foreground, whereas the portion of the image that is much smaller in size are assumed to be in the background. In the video streams, the foreground detection is done by indentifying the Region of Interest (ROI) or the objects in motion (foreground) from the background. The human beings are predicted as the foreground objects in the surveillance systems [1]. There are two major categories of the foreground detection process: Derivative approach and the Background subtraction approach. Derivative algorithm is most elementary approach which was designed based on the assumption that the background remains static throughout the video stream. However, in most cases, the background may not remain static. It may get changed under conditions like lightning, snowing and so on. So, it is essential that the background model must be more robust and adaptive to the changes [2]. In Background subtraction, the foreground object is obtained by subtracting the current image frame from the reference image. Consequently, the background model must be developed in such a way that it represents the scene accurately after all the non static parts are removed. It must be robust and adaptive to the changes like the lighting conditions [3].

There are various challenges that are faced while developing a robust model.

- It must be able to adapt to the rapidly moving objects.
- It must be able to avoid the detection of the slow changing background like tree leaves waving, raining, and shadow and so on.
- The background model should be able to detect the swiftly changing background such as starting and stopping of vehicles [4].

The simplest way in which the background model can be developed is by acquiring the image frame which does not have any non static objects in it. It is considered as the reference frame against which all other frames are compared [4].

The rest of the paper is organized as follows: Section 2 presents a detailed survey of several foreground detection approaches presented by various authors. Section 3 classifies the techniques of the foreground detection. Every technique is discussed briefly. Section 4 highlights the limitations of the Derivative approach. Section 5 addresses the advantages of the Background subtraction approach. Lastly, all the important aspects of the study are highlighted in the conclusion.

2. Literature Survey

Many researchers have presented various foreground detection methods over time. Among those approaches the Background subtraction approach has gained a lot of popularity due to its advantages over the Derivative approach. The concept remains similar of almost every approach, the first or previous frame is used to generate a background reference model. The foreground object is detected by comparing the current frames with the generated background model and then the model is updated.

Many background modeling techniques are classified into different categories such: pixel based, region based and hybrid methods. They can also be grouped as parametric and non- parametric approaches. One of the most popular pixel based method, Gaussian distribution model was first introduced by Wren et al. [22] for modeling the background at each pixel. Since it used only single Gaussian function, it was not adaptive to the sudden changes in the background [23]. The Gaussian mixture model was proposed by Stauffer and Grimson [24], [25] for removing the unnecessary disturbance caused by the background changes like tree leaves waving and water waves. In this method every pixel is modelled with the K Gaussian functions rather than a single Gaussian function [26]. An adaptive Gaussian mixture model was introduced by Zivkovic [27], [28] for updating the GMM parameters. In [29] Lee showed that the convergence rate can be improved without making any changes to the stability of GMM. Maddalena et al. [30] proposed a non parametric approach known as self-organisation through the artificial neural networks.

In 2000, 9 different algorithms were surveyed by Mc Ivor [31]. This survey shows the description and the comparison between the models. In 2004, Piccardi [32] reviewed 7 methods and categorized them on the basis of the speed, memory and the accuracy. This review gives a very good insight to the readers about complexity of the methods. The most appropriate model can be chosen as per the application requirement. In 2005, Cheung and Kamath [4] show that the various methods can be classified into recursive or non-recursive techniques. Followed by this classification, Elhabian et al. [33] presented a survey in the background modelling based on the recursive and the non- recursive techniques. In 2010, Cristani et al. [34] presented a review on several algorithms and classified them in single a monocular sensor or multi-sensors but it is not optimal because some methods can be used in both the categories [2]. Other surveys and comparisons of different algorithms for background subtraction can be found in the literature [35], [36].

3. Foreground Detection Algorithms Classification

The foreground detection algorithms are broadly categorized as the derivative algorithms and the background subtraction algorithms. Both the techniques have different methods included in them [1].

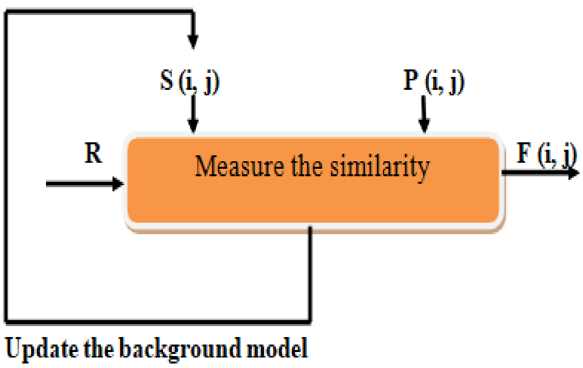


Figure 1 Foreground Detection

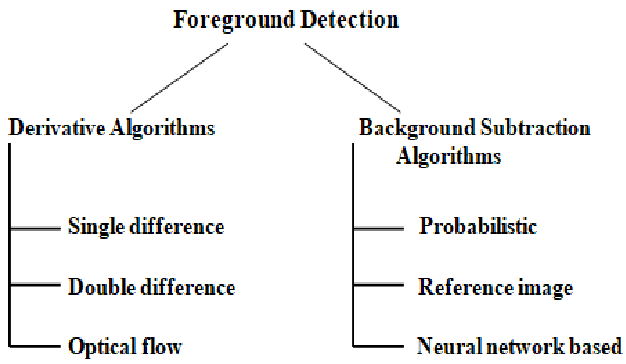
The difficulty of detecting the foreground from the video sequence totally depends upon the type of algorithm used. There are many algorithms designed for this purpose. The general working of the foreground detection process is shown in the Figure 1. S (i, j) stands for the background reference model. At time t, for pixel p (i, j) the S (i, j) is generated. If the current pixel p (i, j) has any similarities with the background model then it is detected as a background pixel. R is the threshold and f (i, j) is the foreground.

IPASJ International Journal of Information Technology (IIJIT)
Web Site: http://www.ipasj.org/IIJIT/IIJIT.htm
A Publisher for Research Motivation ....
Email:editoriijit@ipasj.org
Volume 6, Issue 5, May 2018
ISSN 2321-5976

Two approaches of the Foreground detection process are as follows:

1. **The Derivative algorithms** use a simple concept of comparing the pixels of the current frame with the background frame. However, there is an assumption that the background is entirely still which is not practically true. In reality there is motion in the background also.

2. The **Background subtraction algorithms** were introduced to overcome the drawbacks of the derivative algorithms. The processing of the foreground detection is very convenient and efficient [1].



For these algorithms, the foreground detection process can be expressed by the given equation.

$$Fgnd = I_i - I_j$$

In this equation Ii is the known as the reference image. Reference image does not consist of any foreground object and Ij represents the latest frame which includes the foreground objects to be detected [1].

3.1 Derivative Algorithms

The Derivative Algorithms can be further categorised as:

3.1.1 *Single difference algorithms*: In these type of algorithms, the pixels of the current frame are compared with the pixels of the previous frame in a video. These pixels are categorised as the background or the foreground based on some pre defined threshold [5], [6].

3.1.2 Double difference algorithms: This algorithm is quite similar to the Single difference algorithm. In this algorithm rather than considering a single variation, we compare more than one frame with the adjacent frames [7], [8].

3.1.3 Optical flow algorithms: This algorithm uses the concept of motion vectors and block match. This type of algorithm is explained in [9].

Table 1 briefly introduces the various approaches for Derivative algorithms presented by different authors.

3.2 Background subtraction algorithms

3.2.1 Probabilistic models: In these kind of algorithms the foreground is separated from the background based on the probability distribution function. Two different approaches can be used for this purpose: Parametric approach or a Non-Parametric approach. A widely used parametric approach is based on the Gaussian distributions as shown in [10] whereas few examples of the nonparametric approach are Kernel Density Estimation (KDE) [11] and K-Nearest Neighbor. For these algorithms to work, the current frame is compared to the reference background image. The probability of the pixels is computed based on the probability distribution function of the background. Then, the pixels that have probabilities below a threshold are considered as the foreground and other pixels are known as background.

3.2.2 Reference image models: Single or multiple frames are used to represent the background in these algorithms. The current frame is compared to the background reference frame on the basis of the distance of the color space between the two corresponding pixels. If the color space distance between the each pixel is above the threshold, then it is represented as the foreground [12], [13].

3.2.3 Neural network based models: As the name suggests, this kind of algorithm uses the concept of the neural network to detect foreground in a video stream [14]. A set of random frames is used to train the Artificial Neural Network, and then they separate the foreground pixels from the background pixels [1].
Table 2 briefly introduces the various approaches for Background subtraction algorithms presented by different authors.

Table 1: Derivative algorithms

Technique	**Authors**	**Description**
Single Difference	Liyuan et al.	Two techniques were introduced that can detect any change caused by the integration of the texture and intensity difference of frames. The approaches were much more robust than more general illumination approaches.
Single Difference	Francesco et al.	A signed differencing and connectivity analysis based method was developed to overcome the detection of the ghosts by single difference algorithms.
Double Difference	Xia et al.	The presented method overcomes the limitation of the CAMShift algorithm. It is a method that tracks the moving vehicles using double difference and CAMShift approaches.
Double Difference	Robert et al.	Presents a video surveillance technique using multiple video sensors that continuously tracks vehicles and people in the crowed places.

4. Limitations of Derivative Algorithms

There are various limitations of the Derivative algorithms. They are summarized as:

It is assumed that the background is either totally stationary or it moves very slowly as compared to the foreground but in practical life it is very unlikely.
When the background moves swiftly, the accurate detection of foreground is nearly impossible.

It can cause foreground aperture problem. When an object is temporarily still, it could be mistaken a part of background. It usually occurs when the size the foreground is bigger than the background [1].
False foreground detection can occur when the light conditions changes or even if the tree leaves wave in the background.

Table 2: Background Subtraction algorithms

Technique	Authors	Description
Probabilistic	Stauffer et al.	Adaptive Gaussian Mixture Model that models every pixel as a Gaussian function. Foreground and background pixels are labeled according to the Gaussian distributions.
Probabilistic	Elgammal et al.	The kernel density estimation techniques in order to represent the background and foreground in surveillance of videos. The probability density function of intensity of pixel is estimated from the recent intensities.
Reference Image	Toyama et al.	Wallflower approach was developed to make the predictions of the background based on the probability by using Wiener filtering.
Neural Network	Culibrk et al.	Proposes architecture of a neural network that forms a Bayesian classifier for background subtraction modeling.

Advantages of the Background Subtraction Algorithms:

There are many advantages of the Background detection algorithms over the Derivative approaches. Several problems and the limitation of the derivative algorithms can be solved by the background subtraction algorithms. Many researchers have proposed various methods in [15], [16], [17], [18], [19]. Amongst them the Mixture of Gaussian (MOG), Kernel Density Estimation, SKDA and K-nearest neighbor are some of the popular methods.

Steps for the Background subtraction process

(1) The first step is to obtain the background image by using N frames. Preprocessing and background initialization takes places in this step.
(2) Then, the foreground detection occurs; the pixels are classified as either foreground or background by comparing the current frame with the background reference model.
(3) Lastly, the background maintenance is done so that the background image is updated from time to time.

The steps (2) and (3) are repeatedly over time. Figure 2 shows the steps of the Background subtraction process. The sub steps are explained as follows:

[I] Background Modeling

Background modeling means developing the background model against which all the frames in a video sequence is compared. It can handle the uni-modal or the multi-modal background. This step consists of preprocessing and background initialization. Generally, in background initialization the first frame or the background model is used to initialize the background over some trained frames. The background model initialization becomes a challenge when most of the training contains the foreground object. Some algorithms are as follows:

(1) Batch ones which use N training frames. They could be consecutive or not [2].
(2) Incremental with known N.
(3) Progressive ones with unknown N as the partial backgrounds are generated and the process goes on until a background image is created [20]. Also, the complexity of the background models plays an important role in the background initialization [21].

[II] Foreground Detection
In this step the pixels are classified as the foreground pixels or the background pixels. It is a classification process.

[III] Background Maintenance
Background maintenance is as important as any other step. The data is also validated in this step. The model must be adaptable to the constantly changing scenes. The mechanism used for the process must be achieved on-line and so it must be an incremental one.

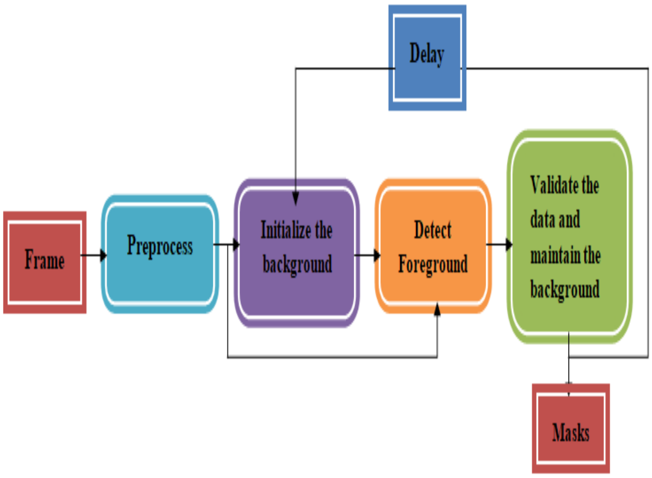


Figure 2 Background subtraction process

Conclusion

This paper briefly discusses the working of the foreground detection process. The two categories: Derivative approach and the Background subtraction approach are discussed and a survey of several background subtraction algorithms elaborated by various researchers has been presented. The limitations and the advantages of various approaches have also been highlighted in the paper.

References

[1] M. Nawaz, J Cosmas, P l. Lazaridis, Z. D. Zaharias, Y. Zhang, H. Mohib. "Precise foreground detection algorithm using motion estimation, minima and maxima inside the foreground object." IEEE Transactions on broadcasting 59.4 (2013): 725-731.
[2] T. Bouwmans, "Traditional and recent approaches in background modeling for foreground detection: An overview." Computer Science Review 11 (2014): 31-66.
[3] M. Vargas, J. M. Milla, S. L. Toral, F. Barrero. "An enhanced background estimation algorithm for vehicle detection in urban traffic scenes." IEEE Transactions on Vehicular Technology 59.8 (2010): 3694-3709.
[4] S. Ching, S. Cheung, and C. Kamath. "Robust techniques for background subtraction in urban traffic video." Visual Communications and Image Processing 2004. Vol. 5308. International Society for Optics and Photonics, 2004.

[5] L. Li and M. K. H. Leung. "Integrating intensity and texture differences for robust change detection." IEEE Transactions on image processing 11.2 (2002): 105-112.
[6] F. Archetti, C. E. Manfredotti, V. Messina, D. G. Sorrenti,. "Foreground-to-ghost discrimination in single-difference pre-processing." International Conference on Advanced Concepts for Intelligent Vision Systems. Springer, Berlin, Heidelberg, 2006.
[7] X. Jie, J. Wu, H. Zhai, Z. Chui. "Moving vehicle tracking based on double difference and camshift." Proceedings of the International Symposium on Information Processing. Vol. 2. 2009.
[8] R. T. Collins, A. J. Lipton, T. Kanade, H. Fujiyoshi, D. Duggins, Y. Tsin, D. Tolliver, N. Enomoto, O. Hasegawa, P. Burt, L. Wixson. "A system for video surveillance and monitoring." VSAM final report (2000): 1-68.
[9] B. K. P Horn, and B. G. Schunck. "Determining optical flow." Artificial intelligence 17.1-3 (1981): 185-203.
[10] C. Stauffer and W. E. L. Grimson. "Adaptive background mixture models for real-time tracking." Computer Vision and Pattern Recognition, 1999. IEEE Computer Society Conference on.. Vol. 2. IEEE, 1999.
[11] A. Elgammal, R. Duraiswami, D. Harwood, L. S. Davis. "Background and foreground modeling using nonparametric kernel density estimation for visual surveillance." Proceedings of the IEEE 90.7 (2002): 1151-1163.
[12] K. Toyama, J. Krumm, B. Brumitt, B. Meyers. "Wallflower: Principles and practice of background maintenance." Computer Vision, 1999. The Proceedings of the Seventh IEEE International Conference on. Vol. 1. IEEE, 1999.
[13] D. Conte, P. Foggia, M. Petretta, F. Tufano, and M. Vento, “Meeting the application requirements of intelligent video surveillance systems in moving object detection,” in Proc. 3rd Int. Conf. Adv. Pattern Recognit. Image Anal., 2005, pp. 653–662.
[14] D. Culibrk, O. Marwues, D. Socek, H. Lalva, B. Furht. "Neural network approach to background modeling for video object segmentation." IEEE Transactions on Neural Networks 18.6 (2007): 1614-1627.
[15] F. C. Cheng, , S. C. Huang, and S. J. Ruan. "Illumination-sensitive background modeling approach for accurate moving object detection." IEEE Transactions on broadcasting 57.4 (2011): 794-801.
[16] H. Ren and G. Xu. "Human action recognition in smart classroom." Automatic Face and Gesture Recognition, 2002. Proceedings. Fifth IEEE International Conference on. IEEE, 2002.
[17] L. Wixson. "Detecting salient motion by accumulating directionally-consistent flow." IEEE transactions on pattern analysis and machine intelligence 22.8 (2000): 774-780.
[18] C. Stauffer and W. E. L. Grimson. "Learning patterns of activity using real-time tracking." IEEE Transactions on pattern analysis and machine intelligence 22.8 (2000): 747-757.
[19] M. Nawaz, J. Cosmas, A. Adnan, M. Ali. "Inter-intra frame segmentation using colour and motion for region of interest coding of video." Broadband Multimedia Systems and Broadcasting (BMSB), 2011 IEEE International Symposium on. IEEE, 2011.
[20] R. M. Colque, G. C’mara-Ch’vez.. "Progressive background image generation of surveillance traffic videos based on a temporal histogram ruled by a reward/penalty function." Graphics, Patterns and Images (Sibgrapi), 2011 24th SIBGRAPI Conference on. IEEE, 2011.
[21] B. Qin, J. Wang, J. Gao, T. Pang, and F. Su. “A traffic video background extraction algorithm based on image content sensitivity”. CSI 2010, pages 603–610, 2010.
[22] C. Wren, A. Azarhayejani, T. Darrell, A.P. Pentland IEEE Trans. Pattern Anal. Mach Intell., 19 (7) (1997), pp. 780-785.
[23] M. Piccardi IEEE Int. Conf. Syst. Man Cybern, 4 (Oct. 2004), pp. 3099-3104 The Hague, The Netherlands.
[24] C. Stauffer, E. Grimson, “Adaptive background mixture models for realtime tracking”, in: Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., vol. 2, 1999, pp. 246e252.
[25] C. Stauffer, E. Grimson, IEEE Trans. Pattern Anal. Mach. Intell. 22 (8)(Aug. 2000) 747e757.
[26] Y. Benezeth, P. M. Jodoin, B. Emile, H. Laurent, C. Rosenberger. "Review and evaluation of commonly-implemented background subtraction algorithms." Pattern Recognition, 2008. ICPR 2008. 19th International Conference on. IEEE, 2008.
[27] Z. Zivkovic, Improved adaptive Gaussian mixture model for background subtraction, in: Proc. 17th Int. Conf. Pattern Recognit., vol. 2, Aug. 2004, pp. 28e31.
[28] Z. Zivkovic, F. van der Heijden, Pattern Recognit. Lett. 27 (May 2006) 773e780.
[29] D.S. Lee, Pattern Anal Mach. Intell. IEEE Trans. 27 (5) (May 2005) 827e832.
[30] L. Maddalena, A. Petrosino, IEEE Trans. Image Process. 17 (7) (2008) 1168e1177.
[31] T. Bouwmans. "Traditional and recent approaches in background modeling for foreground detection: An overview." Computer Science Review 11 (2014): 31-66.
[32] M. Piccardi. "Background subtraction techniques: a review." Systems, man and cybernetics, 2004 IEEE international conference on. Vol. 4. IEEE, 2004.

[33] SY. Elhabian, KM. El-Sayed, and S. H. Ahmed. "Moving object detection in spatial domain using background removal techniques-state-of-art." Recent patents on computer science 1.1 (2008): 32-54.
[34] M. Cristani, M. Farenzena, D. Bloisi, V. Murino. "Background subtraction for automated multisensor surveillance: a comprehensive review." EURASIP Journal on Advances in signal Processing 2010.1 (2010): 343057.
[35] Chalidabhongse, T. H, K.K, Harwood, D. and Davis. L. "A perturbation method for evaluating background subtraction algorithms." Joint IEEE International Workshop on Visual Surveillance and Performance Evaluation of Tracking and Surveillance. 2003.
[36] S. Ching, S. Cheung, and C. Kamath. "Robust techniques for background subtraction in urban traffic video." Visual Communications and Image Processing 2004. Vol. 5308. International Society for Optics and Photonics, 2004.

AUTHORS

Kritika Singh has received her B Tech degree in Information Technology from GGSIPU, New Delhi, India. She was born and brought up in New Delhi, India and she is currently pursuing M Tech Information Security in the Department of Computer Science and Engineering from GGSIPU, New Delhi, India. Her research interests include Network Security, Image processing and Steganography.

Dr. Vishal Gupta is an Associate Professor at AIACT&R, New Delhi, India. He did his B. E. in Computer Science & Engineering from Rohilkhand University, UP. He did his M Tech from University School of Information Technology, GGSIPU, New Delhi, India. He has more than 16 years of experience in teaching. His areas of specialization include Computer Networks, Database Management Systems, Operating Systems, Compiler construction and Information Security.