International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 09 Issue 12 ǁ 2021 ǁ PP. 05-10

Subtraction Algorithm for Human Activity Recognition

Nirvi Kalp
RKDF Institute of Science and Technology
Bhopal, India

Anoop Singh
RKDF Institute of Science and Technology
Bhopal, India

Dr. Varsha Namdeo
RKDF Institute of Science and Technology
Bhopal, India

Abstract: *Foreground Subtraction is very important preprocessing technique in many computer vision based real application. This work proposes an improved foreground Subtraction of video frame sequence captured by UAV Camera. First, the background image is detected for video sequence by background subtraction algorithm. Using background-foreground segmentation of video frame sequence with new pixel value and Gaussian distribution with optional parameter, we get the moving object and its features. It does not require specific camera motion and any background information. The proposed technique first subtract two consecutive frame sequence and gets foreground frame using low pixel value rank approximation technique. Finally, the denoised morphological transformation filtering technique with the image gradient map are used to give output foreground mask and better segmentation results. The experimental output proves that this proposed technique works fairly accurate for moving object detection.*
Keywords: Background subtraction, Foreground extraction, Gaussian distribution, frame sequence

---

Date of Submission: 20-11-2021 Date of acceptance: 05-12-2021

I. Introduction

In practical day to day life foreground-background subtraction is an important task for a large number of computer vision application. Examples of such computer vision applications are object segmentation, pedestrian tracking, counting for the number of vehicles in traffic and visitors in office, identify foreground mask, security enhancement, object parking management. Many algorithm have been developed and their performance was compared based on execution algorithm on datasets which gives the percentages of error rate produced by the various algorithm. This technique process is to depart foreground scene from frame. It is a video processing technique in which researcher focus on static cameras with dynamic background and its associated environmental challenges like camera jitter, object motion, intermittent, illumination changes, shadows etc. Techniques developed for UAV cameras are used for many new computer vision systems. While these new system have been used for new challenging applications, but in many cases, different videos environment changes the performance of the techniques, therefore first it require testing under all different adverse situations. Background-foreground algorithms are not fully able to handle with all real challenging environment including camouflage effects, illumination changes, ghosting artifacts, dynamic background and shadows [1].

The first step of the present approach is a classification of different dataset captured by different environment for a particular application. Many approaches were compared for foreground –background algorithms and found that foreground subtraction segment are moving in different part of interest objects of the present image frame. Those pixel intensity value which fulfil this threshold value are declared foreground and remaining pixels are declared as background. The foreground object must adapt to gradual and sudden change in the foreground. So, foreground approaches may take into consideration after changes at differing spatial scales. To resolve the challenging problem in dynamic foreground-background person counting application, one can estimate an image in which people pass in front of the road street. In this situation, only persons are moving and the process of foreground subtraction is applied and by subtracting person from frame. Although in other application, person and background can also change.

The second features of the present work is collecting own dataset with different motion that gives an appropriate object segmentation techniques to handle with the different challenging environment. For every video frame with their presenting datasets, algorithm choose only the image in which environments can examine the performance of different segmentation technique in those frame sequence. Based on the output data, the proposed technique was found quite effective for moving object detection also. In the present paper

Section 2 presents the related work, the proposed methodology in section 3 and conclusion with some future scope of foreground-background subtraction technique in section 4 respectively.

II. Related Work

In the recent past some techniques have been developed to find and detect the foreground object in video frame sequence. In the video frame sequence, the foreground detection is mostly useful to enhance the performance of motion detection while tracking and detecting. With the development and progress of new technology, the motion detection system is becoming very popular. One of the major difficulties in the motion detection system is that the foreground of the moving object becomes one of the moving object which is a major problem in the area of computer vision and image processing research. In general, moving object detection and recognition from the video sequence is the first step, which shows direct impact on the sub process of visual analysis. Since the moving objects have the noise like shadows and others noise, hence the noise elimination is essential. A powerful noise removal of moving object not only enhance the quality of the foreground object in the frame analysis but also it is important for identification and detection of the moving data in the video frame sequence. So the noise removal is an important and difficult problem in the motion detection [2, 3]. Presently new video frame sequence as a dataset devoted to foreground subtraction is being progressively added to the number of foreground subtraction video frame sequence datasets to address the difficulties of a large real dataset for generating different algorithm. These type of datasets/frame sequence are acceptable to many research problems which help in comparative analysis for the application of other technique on similar frame sequence. The proposed method provides the complete structure of publicly frame sequence as a video dataset, total number of video frame sequence, use of different type of camera, and noise present in the background. The difficulties of change detection, foreground extraction and motion detection are similar and very much associated with foreground subtraction. The method of foreground subtraction works on effective foreground modeling with three different steps [4, 5]: foreground initialization, background detection and foreground maintenance. The first object is to develop a foreground model that divides the frame into fixed number. The foreground model can be developed by different methods like statistical, Neuro inspired, fuzzy etc. In background detection, a comparison is done between the background model and the current frame. The subtraction gives the foreground of the image. During foreground maintenance, frames are also processed to update the foreground model which is found with respect to an error rate at the first step. If any object is not changing during next frame, then it should be attached in the background. Generation of such technique is a major problem and few researchers have dealt with such problem [[6, 7, 8]. However, some report say they are handled on a reduced time complexity on a small dataset for some algorithm, but these works don't tackle many other technique [9]. Background subtraction steps consist a foreground model [15, 16], which can be completed by setting features manually in static image that shows the foreground and background only without moving scene. For every video image sequence, difference between static image and the current frame can be calculated. This technique is called consecutive frame difference [10, 11, 12,13].But when the source lighting changes then the background segmentation may fail and under such circumstances consecutive frame is not the good option. So, if it is possible to use the current frame and previous frame on behalf of a static image, then this technique further called frame difference or image difference which handles many background changes but fails when object is moving. This challenging environment occurs when the same object of the image consists of different colors intensity [17]. In this situation, the foreground subtraction algorithm may segment part of the object of interest as background. Some factors that help for challenging situation are objects with colorful and complex textures. If there are ~~is~~ no moving parts of the frame sequence, many techniques can be used to identify the static part as background. In many applications like car or human counting, it is in general for car that human stopped in image which is to be taken as a background by the technique. Hence, when an object of interest is approximately constant [18, 19, 20], it may counted as a challenging problem.

Present of shadows on frame sequences is also a challenging environment to overcome by foreground subtraction techniques[18,21].Many research articles report specifically the issue of shadow removal, which can be further divide as an object of interest by the technique[22].When the light incident on the object heavily, saturate and hue of the frame changes, it makes shadow removal ~~a~~ very difficult[23].Incidences of source light on human or car is a general factor that affects this challenging environment. Shadows are also co-related to the object detection problem. Other challenging problem is background movements[23,24,25].There are many factor which is associated with this and the~~se~~ reason depends on the situation of the application. Dynamic background can be one of such reason. When the video is captured in outdoor situation, dynamic background may be found by bush movement or by the tree or the wind action [25].Effects of the fog, snow or rain were also shown by the researcher as a factors that causes this type of environment. These type of issue often shown as dynamic background.

III. Proposed approach

In the context of foreground subtraction from UAV-captured video, a new technique is proposed that improve**s** the performance of foreground detection as well as the background subtraction. This approach consists of four phase: Background selection, frame subtraction, foreground update and a foreground filter (Figure 1). This ~~is~~ combine **is** called Gaussian mixture model.

3.1. Background selection: The first objective **is** to find out a background model from video frame sequence. This is designed by fuzzy K-mean algorithm. In K-mean clustering, every pixel in a frame are processed and this works done **is** by the arithmetic mean of the pixels between consecutive frames. Hence for a video B with n number of frames $B=\{P_1,P_2,\ldots..P_n\}$,then the background model M will be

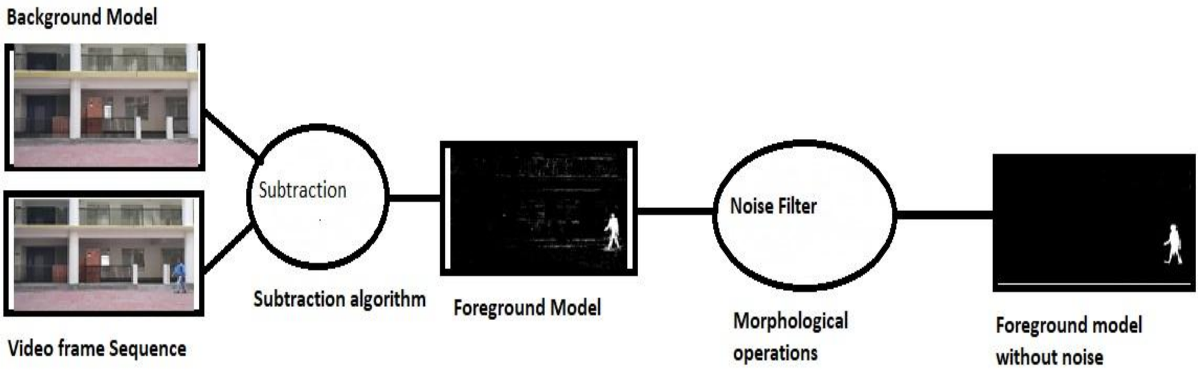

Figure 1: Proposed Approach for foreground subtraction from UAV-captured video sequence

$$M=\frac{1}{n}\sum_{t=0}^{n}P(t) \quad (1)$$

This select**s** the background of the video. After the selection of the background, pixels are updated using the following way:

$$M_t=(1-\alpha)M_{t-1}+\alpha P_t \quad (2)$$

Where M_t is the background model for time t and α is the learning rate and its value lies between 0 to 1. In this technique, only the area with no moving element are computed (Figure 2).

(a)Input Video (b) Background Model

Figure 2: Background Selection after 183 iteration with α=.05

3.2. Frame subtraction: In this steps, a comparison is done between the background model and frame sequence. This subtraction gives the foreground of the frame.

Foreground frame (FF) =Current frame (CF)-background frame (BF) (3)

For every frame sequence, the difference between the current frame and the background frame is calculated. This method is called frame difference. Color, texture and edges features are used to improve the frame subtraction, and in this technique, distributions of every pixel is shown by an addition of weighted Gaussian distribution. This is called Gaussian mixture model (GMM). However, as a new frame is computed, the Gaussian mixture model parameters for every pixel are computed and updated for colors variations (Figure 3). In time t, we suppose that G_t produced for every pixel from the frame $\{P_1, P2 \ldots P_{t-1}\}$, of a pixel, then the new frame pixel is computed as:

$$L\ (P_t) = \sum_{b=1}^{n} \frac{a_b}{(2\pi)^{\frac{d}{2}} |\sum b|^{\frac{1}{2}}} \quad e^{-\frac{1}{2}(P_t-\mu_b)^T} \ \sum \sum^{-1} (P_t - \mu_b) \qquad (4)$$

Here, d is the dimension for color space, μ_n is mean, μ_b and $\sum_b$ is covariance matrix. α_b is weight factor. The colors red, green and blue of each pixel are independent.

Figure 3: Frame subtraction for Frame sequence of datasets

This gives probabilistic background segmentation technique that finds possible foreground elements using Bayesian algorithm.

3.3 Foreground updates:-During the foreground detection, frames are also processed to improve the background found at the first step with respect to a failure rate. An element not changing during time should be attached in the background. Fuzzy function is used to compute the foreground detection and to improve the background. To improve the background with Fuzzy running average which is calculated as

$$FRA(x,y) = \frac{P_t(x,y) - M_{t-1}(x,y)}{T} \qquad (5)$$

Here it is threshold that gives foreground mask (Figure 4).

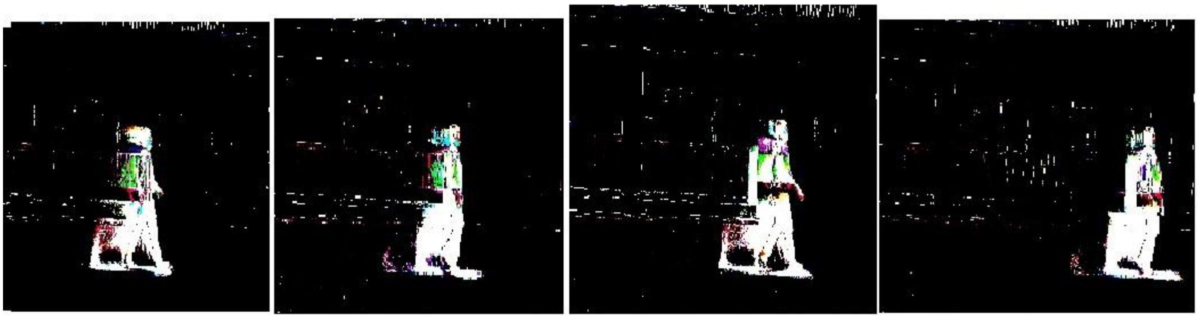

Figure 4: Foreground mask of video some frame sequence

3.4. Foreground Filter: For processing the frame containing only the object, a series of processing frame are averaged. Background frame obtained using equation 6.

$$BF(x,y) = \frac{1}{N} \sum_{j=1}^{N} X(x, y, t - j) \qquad (6)$$

Where N is the number of frames.

Low pass filter is used for noise reduction in the foreground mask (Figure 5) which is calculated using equation 7.

$$FM_t(x,y)=\begin{cases} 1 \; if \; F\left(FRA_t(x,y)\right) > 1 \\ 0 \quad otherwise \end{cases} \tag{7}$$

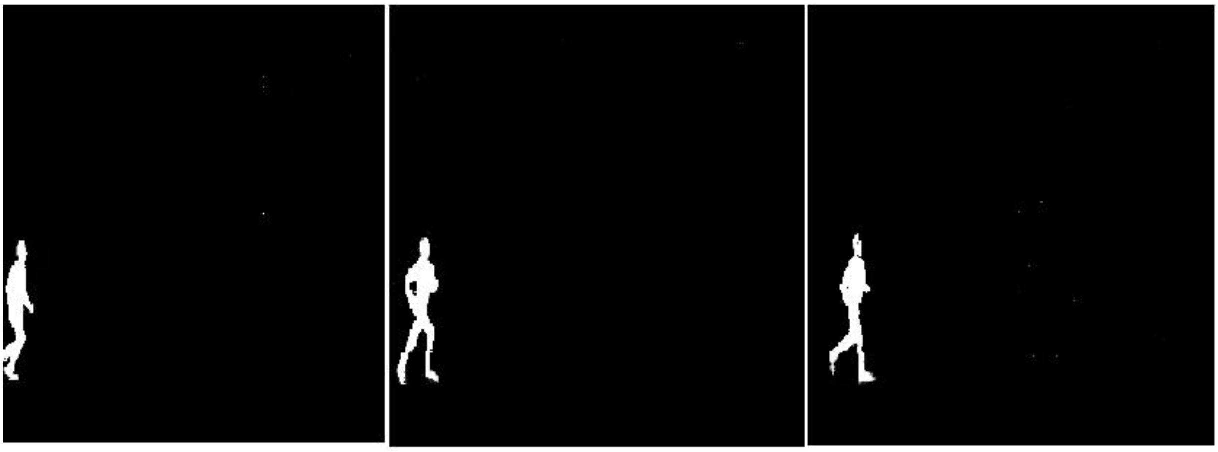

Figure 5: Foreground mask obtained by low pass filter.

IV. Conclusion and Future work

- In this paper, efficient foreground subtraction algorithm using Gaussian mixture model have been processed.
- This technique cover**s** a large time slot. It is found that the actual videos are hardest to handle, giving to lower value.
- It is being observed that the best technique pixel based segmentation also do not always give best result (Figure 6).
- The training of the foreground and background selection are very challenging in many images.

Figure 6: Frame sequence and its corresponding foreground mask for some difficult datasets

- Also it is being seen that shadow removal can be applied only for some datasets.
- An image captured from a mobile camera is a real challenge for foreground subtraction.
- These technique**s** are developed for static background, and the same can be tested by this techniques on moving backgrounds.

References

[1]. P. Dollar, C. Wojek, B. Schiele, and P. Perona, “Pedestrian detection: an evaluation of the state of the art,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 34, no. 4, pp. 743–761, 2012.
[2]. Z. Li, J. Yang, G. Liu, Y. Cheng, and C. Liu, “Unsupervised range-constrained thresholding,” Pattern Recognition Letters, vol. 32, no. 2, pp. 392–402, 2011.
[3]. B.-H. Chen, S.-C. Huang, and J.-Y. Yen, “Counter-propagation artificial neural network-based motion detection algorithm for static-camera surveillance scenarios,”Neurocomputing, vol. 273, pp. 481–493, 2018.
[4]. A. Sobral and A. Vacavant, ‘‘A comprehensive review of background subtraction algorithms evaluated with synthetic and real videos,’’ Comput. Vis. Image Understand., vol. 122, pp. 4–21, May 2014.
[5]. T. Bouwmans, ‘‘Recent advanced statistical background modeling for foreground detection-a systematic survey,’’ Recent Patents Comput. Sci., vol. 4, no. 3, pp. 147–176, 2011.
[6]. Y. Benezeth, P.-M. Jodoin, B. Emile, H. Laurent, C. Rosenberger, Review and evaluation of commonly-implemented background subtraction algorithms. In: IEEE International Conference on Pattern Recognition (ICPR), 2008, pp. 1–4.
[7]. Y. Dhome, N. Tronson, A. Vacavant, T. Chateau, C. Gabard, Y. Goyat, D. Gruyer, A benchmark for background subtraction algorithms in monocular vision: a comparative study, in: IEEE International Conference on Image Processing Theory, Tools and Applications (IPTA), 2010, pp. 66–71.
[8]. A. Prati, I. Mikic, M. Trivedi, R. Cucchiara, Detecting moving shadows: algorithms and evaluation, IEEE Trans. Pattern Anal. Mach. Intell. 25 (7) (2003) 918–923.
[9]. A. Vacavant, T. Chateau, A. Wilhelm, L. Lequièvre, A benchmark dataset for foreground/background extraction, in: Background Models Challenge (BMC) at Asian Conference on Computer Vision (ACCV), LNCS, vol. 7728, Springer, 2012, pp. 291–300.
[10]. S. Calderara, R. Melli, A. Prati, R. Cucchiara, Reliable back ground suppression for complex scenes, in: ACM International Workshop on Video Surveillance and Sensor Networks, 2006.
[11]. H. Zhang, D. Xu, Fusing color and texture features for back ground model, in: International Conference on Fuzzy Systems and Knowledge Discovery, 2006.
[12]. F. El Baf, T. Bouwmans, B. Vachon, Fuzzy integral for moving object detection,in: IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 2008, pp.1729–1736.
[13]. M. Sigari, N. Mozayani, H. Pourreza, Fuzzy running average and fuzzy background subtraction: concepts and application, Int. J. Comput. Sci.Network Security 8 (2) (2008) 138–143.
[14]. A. Lai, N. Yung, A fast and accurate scoreboard algorithm for estimating stationary backgrounds in an image sequence, in: IEEE International Symposium on Circuits and Systems (ISCAS), 1998, pp. 241–244.
[15]. T. Bouwmans, Recent advanced statistical background modeling for foreground detection: A systematic survey, Recent Patents Comput. Sci. 4 (3)(2011) 147–176.
[16]. T. Bouwmans, F. El Baf, B. Vachon, Statistical background modeling for foreground detection: a survey, Handbook of Pattern Recognition and Computer Vision, vol. 4, World Scientific Publishing, 2010, pp. 181–199. Ch. 3.
[17]. Singh M, Nain N, Panwar S (2015) Foreground object extraction using thresholding with automatic shadow removal. In: 2015 11th international conference on signal-image technology & internet- based systems (SITIS), pp 655–662.
[18]. Bloisi DD, Pennisi A, Iocchi L (2017) Parallel multi- modal background modeling. Pattern Recogn Lett 96:45–54.
[19]. Liu Y, Pados DA (2016) Compressed-Sensed-Domain L 1 - PCA video surveillance. IEEE Trans Multimedia 18(3):351–363.
[20]. Mandellos NA, Keramitsoglou I, Kiranoudis CT (2011) A back- ground subtraction algorithm for detecting and tracking vehicles. Expert Syst Appl 38(3):1619–1631.
[21]. Gallego J, Pardas M, Haro G (2012) Enhanced foreground seg- ` mentation and tracking combining bayesian background, shadow and foreground modeling. Pattern Recog Lett 33(12):1558–1568.
[22]. Badura S, Lieskovsky A, Mokrys M (2011) With shadow elimina- tion towards effective foreground extraction. In: 2011 IEEE inter- national symposium on signal processing and information technol- ogy (ISSPIT). IEEE, pp 404–408.
[23]. Ge W, Guo Z, Dong Y, Chen Y (2016) Dynamic background estimation and complementary learning for pixel-wise fore- ground/background segmentation. Pattern Recogn 59:112–125.
[24]. Berjon D, Cuevas C, Mor ´ an F, Garc ´ ıa N (2018) Real- ´ time nonparametric background subtraction with tracking-based foreground update. Pattern Recog 74:156–170.
[25]. Thangarajah A, Wu QJ, Singh A, Mandon B, Chowdhury A (2015) Video foreground detection in non-static background using multi- dimensional color space. Procedia Computer Science 70:55–61.