Statistically tuned Gaussian background subtraction technique for UAV videos

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Abstract. Background subtraction is one of the efficient techniques to segment the targets from non-informative background of a video. The traditional background subtraction technique suits for videos with static background whereas the video obtained from unmanned aerial vehicle has dynamic background. Here, we propose an algorithm with tuning factor and Gaussian update for surveillance videos that suits effectively for aerial videos. The tuning factor is optimized by extracting the statistical features of the input frames. With the optimized tuning factor and Gaussian update an adaptive Gaussian-based background subtraction technique is proposed. The algorithm involves modelling, update and subtraction phases. This running Gaussian average based background subtraction technique uses updation at both model generation phase and subtraction phase. The resultant video extracts the moving objects from the dynamic background. Sample videos of various properties such as cluttered background, small objects, moving background and multiple objects are considered for evaluation. The technique is statistically compared with frame differencing technique, temporal median method and mixture of Gaussian model and performance evaluation is done to check the effectiveness of the proposed technique after optimization for both static and dynamic videos.

Keywords. Tuning factor; background segmentation; unmanned aerial vehicle; aerial surveillance; thresholding.

1. Introduction

Background subtraction is a method used to segment moving objects in a video taken by a camera by comparing initial frame with the last frame. Background subtraction is a major technique in vision systems and video surveillance. In surveillance systems, the primary objective is to continuously detect the moving object in a video. In the field of aerial surveillance, it helps in understanding the movement of people to uncover suspicious events. The work is designed to process the videos captured by unmanned aerial vehicle (UAV). An unmanned aerial vehicle (commonly named as drone) is an aircraft without onboard human pilot either controlled by

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computers autonomously, or under the remote control, or pilot on the ground. UAV can communicate with its controller and return electro-optic or thermal TV images payload data like position, airspeed, heading and altitude.

Since UAV captures the video dynamically, where both the object and the background keeps moving, real time systems are required to track objects effectively under such dynamic conditions. A traditional segmentation technique involves differencing two frames which works effectively on static background with fixed camera and moving object. Here, all information other than the object to be tracked remains stationary. Thus, finding difference of adjacent frames is easier. But, Aerial surveillance is a vivid environment where all the criteria are dynamic. The segmentation is done for the video captured by unmanned aerial vehicle with varying altitudes and angle of view. Here the camera is in motion to track the moving object in a moving background. Thus, traditional technique introduces ghosting effect and also the noises cannot be eliminated. This requires an adaptive measure to update the background repeatedly based on the initial frame and the last frame. This adaptive measure is implemented by a tuning factor (α). The optimal tuning factor ranges from 0 to 1. The optimal value differs for static and dynamic videos. This paper involves the optimization of tuning factor that suits for both static dynamic videos. The optimization is done by evaluating the extracted statistical textures in each input frame. Based on the optimization, an adaptive Gaussian-based background subtraction technique is proposed. This running Gaussian average based background subtraction technique involves updating at both model generation phase and subtraction phase with tuning factor and Gaussian update, respectively. As only statistical properties are involved in optimizing the tuning factor and Gaussian update factor the implementation of algorithm is easier and works effectively in eliminating noise and other undesired effects. The statistical performance evaluation is done with frame differencing technique, temporal median method and mixture of Gaussian model to check the effectiveness of the proposed technique for both static and dynamic videos. The algorithms are tested with four sample videos of vivid nature like as cluttered background, small objects, moving background and multiple objects.

2. Related work

In this section, we review related work on various techniques involved in background subtraction of videos. Frame averaging process for colour images proposed by Anuva Chowdhury *et al* (2011) learns the variation of each pixel in terms of average in differences between colour of pixels. HSV-based processing is done and morphological operations were performed at the later stages. Shengyong Chen *et al* (2012) proposed a background segmentation method based on hierarchical model. The background update is done by mean shift technique and histogram based background subtraction. Here, the pixel descriptors were determined only for neighbouring pixels. A block based approach proposed by Weihua Xiong *et al* (2010) tries to overcome the drawbacks of consecutive frame subtraction by normalizing cross correlation coefficient. The non-parametric background modelling approach proposed by Martin Hofmann *et al* (2012) involves modelling of foreground by the history of recently accessed pixels. Shinya Miyamoori *et al* (2011) realized a robust approach based on bipolar radial research correlation which involves evaluation with respect to local pixels thereby suppressing the effects of illumination. Songyin Fu *et al* (2010) implemented background subtraction with Gaussian update and statistical model based on pixel changes. Shahrizat Shaik Mohammed *et al* (2010) developed a background subtraction system with mixture of Gaussians, deviation scaling factor and max-min background model for outdoor environment. Selection of detection threshold is a difficult

Figure 1. Workflow diagram.

task which is done easier by Syed Shazali *et al* (2011) by adopting the mean of video statistics. Also, a foreground model was introduced based on small spatial neighbourhood. Yongquan Xia *et al* (2010) proposed a Boolean based method to segment the objects with static scenes. Also, morphological processing was done for filtering and post processing.

The Gaussian mixture model of Stauffer & Grimson (1999a, b) and kernel densities of Elgammal *et al* (2000) are the popular techniques for pixel level modelling. These techniques are equipped to manage slow illumination changes that can be adapted by updated model parameters.

Vijverberg *et al* (2009) proposed a technique to estimate the illumination change by the assumption that the foreground is very small compared to total frame size and results in a uniform histogram across the difference image by fitting Gaussian and Laplacian functions over

Table 1. Properties of input videos.

Property	Video 1	Video 2	Video 3	Video 4
No of frames	87	60	75	101
Frame rate	25 fps	25 fps	25 fps	25 fps
Size	320 × 240	320 × 240	432 × 240	432 × 240

Table 2. Statistical computation of tuning factor.

Algorithm	Video	Mean	Variance	Standard deviation	Tuning factor
FD	Video 1	127.95	6356.547	79.7279	0.738
	Video 2	150.818	2408.442	49.076	0.81
	Video 3	125.273	1161.160	34.076	0.89
	Video 4	120.545	3394.355	58.261	0.86
TMF	Video 1	128.363	4771.194	69.07	0.55
	Video 2	142.545	3026.736	55.016	0.62
	Video 3	122.455	1415.879	37.628	0.68
	Video 4	119.727	1609.446	40.118	0.70
MOG	Video 1	100.591	5110.539	71.488	0.871
	Video 2	150.273	2260.970	47.550	0.92
	Video 3	132.682	1425.465	37.755	0.846
	Video 4	125.591	3789.396	61.558	0.88
AGBG	Video 1	135.091	5123.039	71.575	0.602
	Video 2	137.864	2772.981	52.659	0.507
	Video 3	125.727	1084.398	32.930	0.498
	Video 4	124.955	1786.522	42.267	0.528

the histogram of the frame difference. Parameswaran *et al* (2010) used intensity ratios in the modelling but only as a constant with respect to spatial values. The frequently used and famous background subtraction techniques are listed and reviewed by Massimo Piccardio (2004). Sen-Ching *et al* (2004) discussed on probabilistic approach for robust change in shape, orientation and illumination. Also, the technique deals with detecting non-stationary objects such as swinging leaves, rain, snow and shadow cast. Olivier Barnich & Mark Van Droogenbroeck (2011) provided a universal approach with hardware realization perspective.

Stauffer & Grimson (1999a, b) proposed a method of defining image model consisting of description about both foreground and background values specially designed for the cases of cluttering background like snow and rain. The method proposed by Cucchiara *et al* (2003)

Figure 2. Video 1 of sample 1.

Figure 3. Video 1 of sample 2.

computes a median for special set of values. This is done to increase stability but a buffer is needed.

2.1 Frame differencing

Frame differencing is the basic technique which involves subtraction of adjacent frames to provide the background model. For input video of n frames $F_1, F_2, \dots, F_n$, B_i is initial background model. The final background model B_{i+1} is obtained by the difference between two consequent frames for $i = 1, 2, \dots, n$

$$B_i = F_i, i = 1, \quad (1)$$

$$B_{i+1} = F_{i+1} - F_i, \quad (2)$$

Figure 4. Video 1 of FD – BG model.

Figure 5. Video 1 of TMF – BG model.

where F_i is the i^{th} frame and F_{i+1} is the $i + 1^{\text{th}}$ frame. The background update G_i is obtained by subtracting the subsequent frames F_i with the background model B_i

$$G_i = F_i - B_i. \quad (3)$$

The resultant binary image R_i is obtained by applying the fixed threshold T .

$$R_i = \begin{cases} 1, & G_i > T \\ 0, & G_i < T. \end{cases} \quad (4)$$

Figure 6. Video 1 of MOG – BG model.

Figure 7. Video 1 of AGBG – BG model.

2.2 Temporal median filtering

The temporal median filtering evolves classification of target and shadows and definition of background model accordingly.

The known objects is defined as

$$K_0^t = \{MVO^t\} \cup \{MVO_{sh}^t\} \cup \{G^t\} \cup \{G_{sh}^t\}. \quad (5)$$

For the set of S elements, $I^t(p)$ is the image pixels, $B^t(p)$ is the background pixel and w_b is the weight.

$$S = \{I^t(p), I^{t-\Delta t}(p), \dots, I^{t-n\Delta t}(p)\} \cup w_b \{B^t(p)\}. \quad (6)$$

Figure 8. Video 1 of Output – FD.

Figure 9. Video 1 of Output – TMF.

The final background model is obtained as in (7)

$$B^{t+\Delta t}(p) = \begin{cases} B_s^t(p), & \text{if } p \in 0 \text{ in } \{MVO^t\} \cup \{MVO_{sh}^t\} \\ B_s^{t+\Delta t}(p), & \text{if } p \in 0 \text{ in } \{G^t\} \cup \{G_{sh}^t\}. \end{cases} \quad (7)$$

2.3 Mixture of Gaussians model

Mixture of Gaussians involves multivalued background model generation for multiple background objects. It is done by defining an image model which describes both values of foreground

Figure 10. Video 1 of Output – MOG.

Figure 11. Video 1 of Output – AGBG.

and background based on Massimo Piccardio (2004). The probability of a pixel x at time t is,

$$P(x_t) = \sum_{i=1}^k \omega_{i,t} \eta(x_t - \mu_{i,t}, \varepsilon_{i,t}). \quad (8)$$

K is the Gaussian distribution ranging from 3 to 5 and w_i is the peak amplitude. $\varepsilon_{i,t}$ is the covariance matrix. μ is the mean.

If B distributions are considered, the assigned threshold value T should satisfy,

$$\sum_{i=1}^B \omega_i > T. \quad (9)$$

Figure 12. Video 2 of sample 1.

Figure 13. Video 2 of sample 2.

Figure 14. Video 2 of FD – BG model.

Figure 15. Video 2 of TMF – BG model.

Figure 16. Video 2 of MOG – BG model.

Figure 17. Video 2 of AGBG – BG model.

Figure 18. Video 2 of Output – FD.

Figure 19. Video 2 of Output – TMF.

2.4 Proposed technique - adaptive gaussian average background segmentation

The basic idea is to subtract the input frame with the reference frame. The basic steps include background modelling, update, subtraction and thresholding. The 'n' number of frames in the video sequence is considered for analysis. The n frames are named as $f_1, f_2 \dots, f_n$. The input frames are converted into Gray scale.

2.4a Background modelling: Background modelling is the first step in background subtraction. It constructs the reference image representing the background. Let b_i be the i^{th} background model. It is obtained from the input i^{th} frame f_i .

At initial level $i = 1$ and increases linearly.

$$b_i = f_i, i = 1. \quad (10)$$

Figure 20. Video 2 of Output – MOG.

Figure 21. Video 2 of Output – AGBG.

The final background model b_{i+1} is obtained by the resultant input frame f_i and the assumed background model b_i . Here, $i = 1, 2 \dots, n$. The influence of the input frame f_i and the priority assumed background model b_i are proportioned with the tuning factor α . The value of α decides the extent that both the frames can influence in the next background model. In general α varies from 0 to 1.

$$b_{i+1} = \alpha f_i + (1 - \alpha) b_i. \quad (11)$$

If $\alpha = 0$, then $b_{i+1} = b_i$, thus there will be no updation in background model. This results in ghosting effect. If $\alpha = 1$, then $b_{i+1} = f_i$. Hence the background model and the input frame are same and the result reduces to Boolean 0. Thus it is necessary to update the tuning factor to get the desired result.

Figure 22. Video 3 of sample 1.

Figure 23. Video 3 of sample 2.

2.4b Background update: Let the background update be g_i . It is obtained by subtracting the subsequent input frames f_i with the tuned background model b_i .

$$g_i = f_i - b. \quad (12)$$

2.4c Thresholding: Thresholding is a process used to classify the input pixels into background or object based on the value assumed as threshold 'Th'. Generally, the pixels with values above 'Th' are considered as foreground and the pixels with values below Th are considered as background. The fixed threshold will not produce efficient segmentation for various lighting

Figure 24. Video 3 of FD – BG model.

Figure 25. Video 3 of TMF – BG model.

conditions. Thus, we consider an adaptive approach to update the threshold value based on the statistical properties of the input frame and background model. The resultant binary image r_i is obtained based on the value of threshold Th .

$$r_i = \begin{cases} 1, & g_i > Th \\ 0, & g_i < Th. \end{cases} \quad (13)$$

The adaptive threshold is decided as the average standard deviation of each video frame. The value of σ is updated for each frame.

$$Th = mean(\sigma), \quad (14)$$

$$\sigma_{i+1}^2 = \alpha (f_i - b_i)^2 + (1 - \alpha) \sigma_i^2. \quad (15)$$

Figure 26. Video 3 of MOG – BG model.

Figure 27. Video 3 of AGBG – BG model.

3. Optimization of tuning factor

Optimization of the tuning factor α is very important in background modelling and update. Since in aerial videos both the object and background are dynamic, the traditional process of subtracting two subsequent frames will not be effective. Thus, to classify the background and object it is necessary to obtain the statistical features of the image. The statistical properties of the object differ widely from the background. Let $X_{ij:n}$ be the gray scale vector for the pixel location (i,j) for n input frames. With $E[.]$ as expectation function, $E_{ij}[X_{ij:n}]$ is the mean of a vector of grayscale pixel intensity at pixel location (i,j) for n frames. The tuning factor α is obtained as

$$\alpha_{ij}(n) = \{X_{ij:n} - E_{ij}\} U_x. \quad (16)$$

Figure 28. Video 3 of Output – FD.

Figure 29. Video 3 of Output – TMF.

X_{ijn} is the pixel intensity of n th frame at location (i,j) . E_{ij} is the mean of intensities of n frames at location (i,j) . By evaluating the variance and standard deviation for each frame, and by normalizing

$$\alpha = (X_{ijn} - E_{ij}) / \sigma_{ij}. \quad (17)$$

The value of α is optimized and varies from 0 to 1 for both static and dynamic background models.

4. Implementation

Four videos are considered for analysis. Two of them are with static background and the other two are with dynamic background taken from UAV. The videos with dynamic background are

Figure 30. Video 3 of Output – MOG.

Figure 31. Video 3 of Output – AGBG.

transmitted with the transmission frequency of 1.2 GHz from UAV with altitude ranging from 5 to 50 m. The properties of the videos are listed in the table 1.

5. Results and discussion

The output is obtained by simulation using MATLAB 2010 in a standalone PC with 4 GB Intel Core Duo processor. In each video, 25 frames are considered for analysis. In each frame 100 pixels at random locations are considered and their intensities are taken for processing. Based on the considered pixel values, the statistical calculations are made to determine mean, standard deviation and variance. Based on these three factors, the tuning factor is determined. Table 2 shows the statistical values obtained for videos with static background and videos with dynamic background for the four algorithms considered.

Figure 32. Video 4 of sample 1.

Figure 33. Video 4 of sample 2.

Figure 34. Video 4 of FD – BG model.

Figure 35. Video 4 of TMF – BG model.

Figure 36. Video 4 of MOG – BG model.

In table 2, for the algorithm adaptive Gaussian background subtraction the average tuning factor for video 1 is 0.602, for video 2 is 0.507, for video 3 is 0.498 and for video 6 is 0.528. These values are the average of a sample of 25 frames in each video. The overall tuning factor is approximately around 0.53. Thus, while defining the value for α , it may be assigned varying range from 0.5 to 0.6 for efficient segmentation.

Based on the tuning factor and Gaussian update derived, the running Gaussian averaging background segmentation is implemented for the static and dynamic background videos. Also, the results of existing techniques like frame differencing, temporal median filter and mixture of

Figure 37. Video 4 of AGBG – BG model.

Figure 38. Video 4 of Output – FD.

Gaussian models are obtained. The optimization of tuning factor is not suitable for other techniques since the value α is not used. The tuning factor is optimized to improve the efficiency of the proposed techniques compared to others.

Four videos are considered for analysis (figures 1). Video 1 (figures 2 and 3) consists of static background and the target is larger in size. The corresponding background models are shown in (figures 4–7) and the final subtracted images are shown in (figures 8–11). Video 2 (figures 12 and 13) consists of static background and the target is smaller in size. The background is cluttered and consists of overlapping information. The corresponding background models are shown in (figures 14–17) and the final subtracted images are shown in (figures 18–21). Video 3 (figures 22 and 23) consists of dynamic background and the target is larger in size. There is a single target in the video. Both the background and the target are moving. The corresponding background models are shown in (figures 24–27) and the final subtracted images are shown in (figures 28–31). Video 4 (figures 32 and 33) consists of dynamic background and the target is larger in size. There

Figure 39. Video 4 of Output - TMF.

Figure 40. Video 4 of Output – MOG.

are multiple moving objects in the video. The background is cluttered. Both the background and the target are moving. The corresponding background models are shown in (figures 34–37) and the final subtracted images are shown in (figures 38–41).

To evaluate the effectiveness of the proposed algorithm tuned with α with respect to the other algorithms, some performance evaluation parameters like Peak Signal to Noise Ratio, Root Mean Square Error and Universal Image Quality Index of the input and output were calculated.

The Root Mean Square Error is calculated as,

$$RMSE = \sqrt{\frac{1}{MN} \sum_{j=1}^M \sum_{k=1}^N (x_{jk} - x'_{jk})^2}, \quad (18)$$

where, M and N are the total pixels to be considered.

Figure 41. Video 4 of Output – AGBG.

Table 3. Statistical features of output frames.

Algorithm	Video	MSE	RMSE	PSNR	UIQI
FD	Video 1	139.719	11.820	26.678	0.1668
	Video 2	84.490	9.19	28.863	0.0564
	Video 3	126.93	11.266	27.095	0.1193
	Video 4	127.125	11.231	27.088	0.144
TMF	Video 1	138.624	11.774	26.712	0.171
	Video 2	83.954	9.163	28.89	0.614
	Video 3	126.524	11.248	27.109	0.119
	Video 4	126.982	11.268	27.093	0.152
MOG	Video 1	138.126	11.753	26.72	0.189
	Video 2	83.126	9.117	28.933	0.686
	Video 3	126.114	11.23	27.123	0.123
	Video 4	126.148	11.232	27.122	0.175
AGBG	Video 1	137.229	11.714	26.756	0.193
	Video 2	82.483	9.08	28.967	0.072
	Video 3	125.652	11.209	27.139	0.123
	Video 4	125.534	11.204	27.143	0.185

The Peak signal to Noise ratio is the commonly used performance measure and it is evaluated as

$$PSNR = 10 \log 255^2 / MSE. \quad (19)$$

The universal image Quality Index (Q) is calculated for the series of input images $X = x_i$, and output frame y_i . The range of 'i' varies from 1 to N, where N is the total number of frame pairs considered for analysis.

$$Q = \frac{4\sigma_{xy}.XY}{(\sigma_x^2 + \sigma_y^2)(X^2 + Y^2)}, \quad (20)$$

σ_{xy} is the cross correlation, σ_x and σ_y are the correlation of x and y, respectively. X and Y are the mean value of x and y, respectively.

In each video, 25 frames are considered for evaluation and the average performance values are listed in table 3.

The table 3 shows that the algorithm tuned with α provides effective segmentation. More over the computation time is less. The quality of segmentation is good comparatively as the signal to noise ratio is high and the mean square error is less. Rather than other techniques, the algorithm suits better for aerial surveillance applications due to high speed of computation since the complexity is less.

6. Conclusion

We have portrayed an efficient algorithm with tuning factor and Gaussian update for aerial surveillance. The optimization of tuning factor is done by extracting the statistical features of the input frames. The optimized value of tuning factor is found to be 0.5 to obtain efficient segmentation in adaptive Gaussian background subtraction. The statistical analysis depicts that the algorithm when added with tuning factor is efficient for both static and dynamic videos. It works efficiently for videos which are of dynamic nature completely. Since aerial videos are of that category the proposed technique works dynamically with less computational complexity and provides good quality of segmentation thus can be utilized for real time tracking.

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