International Journal of Image Processing and Vision Science

Volume 1 | Issue 4 Article 15

October 2012

AN ADAPTIVE BACKGROUND UPDATION AND GRADIENT BASED SHADOW REMOVAL METHOD

SUMIT KUMAR SINGH
Computer Engineering Department, IIT Roorkee, Roorkee, India, sumitias89@gmail.com

MAGAN SINGH
Computer Engineering Department, IIT Roorkee, Roorkee, India, magansingh666@gmail.com

AN ADAPTIVE BACKGROUND UPDATION AND GRADIENT BASED SHADOW REMOVAL METHOD

SUMIT KUMAR SINGH[1], MAGAN SINGH[2]

[1,2]Computer Engineering Department, IIT Roorkee, Roorkee, India
E-mail: sumitias89@gmail.com, magansingh666@gmail.com

Abstract- Moving object segmentation has its own niche as an important topic in computer vision. It has avidly being pursued by researchers. Background subtraction method is generally used for segmenting moving objects. This method may also classify shadows as part of detected moving objects. Therefore, shadow detection and removal is an important step employed after moving object segmentation. However, these methods are adversely affected by changing environmental conditions. They are vulnerable to sudden illumination changes, and shadowing effects. Therefore, in this work we propose a faster, efficient and adaptive background subtraction method, which periodically updates the background frame and gives better results, and a shadow elimination method which removes shadows from the segmented objects with good discriminative power.

Keywords- *Moving object segmentation, adaptive background updation, gradient magnitude, shadow removal, background subtraction and updation.*

I. INTRODUCTION

The detection of moving objects in a video sequence is an important research field due to its applicability to automated visual surveillance systems, traffic monitoring systems, sports event interaction, human-computer interaction, crime prevention systems and in many such areas. It has its applications ranging from mundane tasks to highly specialized operations. It is one of the most important research areas of computer vision. For most computer vision-based applications, moving object segmentation is of great importance for the subsequent processes of analysis, recognition, and tracking of objects. As it is the initial stage of most of the computer vision applications, so accuracy and performance of this step decides the accuracy and performance of the subsequent processing operations. Background subtraction as one of the most important techniques has attracted considerable attention of researches. It is one of the most widely used method for moving object segmentation. It can extract pixels in the image sequences with the most discriminative power, but it is extremely sensitive to sudden illumination variations and dynamic environment. If background is not updated properly, it may result into illumination effect, ghost of moving objects effect and many more such effects.

Illumination effect is caused by sudden change in the lightening conditions, in which background pixels are erroneously considered as foreground pixels. Ghost of moving objects, as shown in Fig. (1), appears when pixels belonging to the moving objects, which are detected in the previous frame, are included in the current background frame, which leads to improper segmentation of moving objects. These methods are also affected by shadows cast by moving objects. They detect shadows of moving objects as part of foreground object. Shadows of two or more than two objects may overlap each other and thus results in the false interpretation of a single object. Therefore removal of these shadows becomes an inevitable task, because they can significantly distort shape and geometrical properties of the objects. How to correctly and efficiently update the background model and how to deal with shadows are two of the most distinguishing and challenging aspects of these approaches. Our approach adaptively calculates the background and updates it according to the changing environmental conditions and also detect and removes shadows form the detected moving objects. Therefore, our method addresses both these issues.

II. LITERATURE REVIEW

In recent years, a spate of methods have been proposed to segment moving objects. Gaussian mixture model (GMM) [1] is one of the most popular models for moving objects segmentation, which model the color of every pixel in the image with a mixture of Gaussians model. To consider the color information in background modeling, McKenna et al. [2] used an adaptive background subtraction technique for detecting groups of people by estimating three variance parameters of the R, G, and B channels for each pixel in

(A)ORIGINAL BACKGROUND (B) GHOST OF MOVING VEHICLES
FIG 1: GHOST OF MOVING VEHICLE EFFECT ON BACKGROUND FRAME IMAGE SEQUENCES.

In their background model, recursive updates are used to adaptively cope with changes in illumination. Liption et al. [3] segmented moving targets from a real-time video stream using the pixel-wise difference between consecutive frames. Their method can classify humans, vehicles, and back-ground clusters. Deng-Yuan Haung et al. [4] have proposed a method for detecting moving vehicles based on the filtering of swinging trees and raindrops. But the background calculation and updation process is computationally expensive and does not take into account sudden changes in the illumination conditions and suffer from problems such as ghost of moving objects and shadowing effects. Surendra Gupte et al. [5] presented algorithm for vision-based detection and classification of vehicles. Processing has been performed at three levels: raw images, region level and vehicle level. Its processing is fast, but it is vulnerable to sudden illumination change. Wei Zhang et al. [6] have addressed the problem of moving vehicles segmentation in dynamic scenes.

They have performed dynamic background update. Their method does not consider removal of shadows which can distort the shape of detected moving objects. Seki et al. in [7] presented a background subtraction method for detection of foreground objects in dynamic scenes involving swaying trees and fluttering flags.

They have used the property that image variation at neighboring image block have strong correlation. They have then proposed a method that calculates the likelihood of background and dynamically narrows the permissible range of background image variation.

Shadows can distort the shape of moving objects and affect the subsequent task of object tracking. Cucchiara et al. [8] proposed a method that uses the features of statistics, adaptivity, and selectivity to detect moving objects, ghosts, and shadows. In their method, they adopted color information for both background subtraction and shadow detection to improve the performance of object segmentation and background update. Andres Sanin et al. [9] proposed a shadow detection method which first uses chromaticity information to create a mask of candidate shadow pixels, followed by employing gradient information to remove foreground pixels that were incorrectly included in the mask. Hsieh et al. [10], in their method separated the blobs into individual objects before doing the geometric analysis. Their work assumes that the objects of interest are persons and that their shadows have a different orientation. Leone and Distante [11] have proposed a texture based method which correlates textures using Gabor functions. The method first creates a mask with the potential shadow pixels in the foreground. Then, if the textures of small region centered at each pixel are correlated to the back-ground reference, the pixels are classified as shadow.

III. OVERVIEW OF THE PROPOSED APPROACH

Fig. 2 shows the flowchart of the proposed approach. Initially the background frame is calculated by taking the pixel wise mode of the initial few frames. It serves as the initial background frame for the algorithm.

Then using the background frame and current video frame, difference frame is calculated. Then on applying the threshold value to the difference frame, moving objects are segmented.

The difference frame is also used to update the background frame. Background updation is the most important step of moving vehicle segmentation. Background frame must be adapted according to the changing environmental conditions. If background frame is not periodically updated, it may badly affect the accuracy of object segmentation algorithm. Therefore special attention is paid to background updation stage.

These segmented moving objects may also contain shadows which are also detected as part of the moving objects, which may badly affect the object detection accuracy of this method.

Therefore, shadows needs to be removed from the detected moving objects. So gradient magnitude based calculation is performed on the current foreground and background frame, as a result we get shadow-free moving objects identified.

IV. PROPOSED APPROACH

The proposed system perform its working in two stages:
1) Background subtraction and updation
2) Shadow Removal

A. BACKGROUND SUBTRACTION AND UPDATION

Background subtraction is widely used method for moving object segmentation. Moving object segmentation method segments the moving objects into foreground and background objects. It is one of the initial tasks in vision based applications, which make it critical part of the system. Here we have improved the method given in [6]. In our method we have intelligently applied the background updation, so that unnecessary calculations are avoided, which results in the performance improvement. The success of moving vehicle segmentation depends upon accurately modeling the background frame. The updation process must be fast enough to operate in real time, and be insensitive to lightening conditions. Therefore, we have updated the background periodically to adapt itself for the dynamic environment.

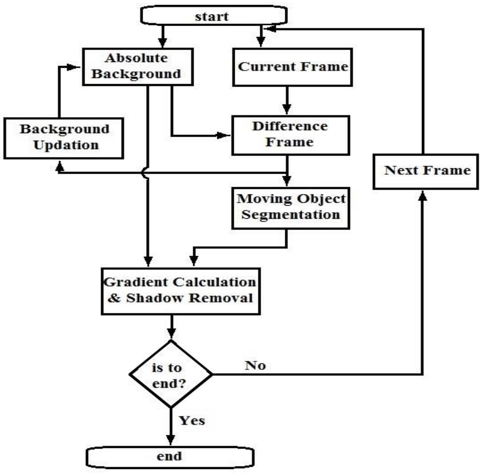


Fig. 2: Flowchart of the proposed system

Before starting moving object segmentation, it is necessary to detect moving pixels. For this we have used background subtraction method. Here we use the following steps:

a) Let B_c, F_n, and Γ_n be current background frame, the nth frame, and moving region in the nth frame. Γ_n is computed as:

$$\Gamma_n(i,j) = \begin{cases} 1 & \text{if } |B_c(i,j) - F_n(i,j)| > \tau_b \\ 0 & \text{else} \end{cases} \quad (1)$$

$\Gamma_n(i,j) = 1$, tells us that there is sufficient difference in the gray intensity of current and background pixel. Therefore, pixel belongs to foreground object, otherwise pixel belongs to background object. τ_b is a threshold value calculated using Otsu's method [12].

b) From (1), we observe that background frame B_c has significant effect on Γ_n. Therefore background must be updated periodically to adapt to the changing illumination conditions and dynamic environment, which is done as below.

c) First, motion mask (Ω_n) is calculated, which is obtained using difference frame (M_n^B) and difference of current and previous frame (M_n^F). Motion mask gives us information about the pixels which are moving and belong to foreground objects.

$$\Omega_n = M_n^B \,\&\, M_n^F \quad (2)$$

$$M_n^B(i,j) = \begin{cases} 1 & \text{if } |Fn(i,j) - Bc(i,j)| > \xi b, \\ 0 & \text{else} \end{cases} \quad (3)$$

$$M_n^F(i,j) = \begin{cases} 1 & \text{if } |Fn(i,j) - Fn - 1(i,j)| > \xi f, \\ 0 & \text{else} \end{cases} \quad (4)$$

Here both the threshold values ξb and ξf are calculated using Otsu's method given in [12].

Therefore, the pixels for which motion mask (Ω_n) is 1,are the pixels which are moving and belong to foreground frame, otherwise they are pixels belonging to background frame.

d) Now instantaneous background (IB_n) is calculated by sampling current video frame (F_n) and current background frame (B_c) according to Ω_n. IB_n is used to update background frame.

$$IB_{n(i,j)} = \begin{cases} F_{n(i,j)} & \text{if } \Omega_n(i,j) = 0 \\ B_{c(i,j)} & \text{if } \Omega_n(i,j) = 1 \end{cases} \quad (5)$$

Instantaneous background plays very crucial role in updating the background. According to eq.(5), pixels for which Ω_n is 1, means that pixel belong to foreground object and it does not play any role for background updation, therefore at that pixel current background frame must be considered. If Ω_n is 0, means that pixel belong to background object and it is used for the background updation procedure, therefore at that pixel current foreground frame must be considered.

e) The crucial part of the algorithm is background updation. Therefore, in the normal condition, when there is no dynamic change in the background, instantaneous background becomes the current background, $B_C = IB_n$. But when lightening conditions change suddenly, we have to update background frame to avoid background pixels to be detected as foreground objects.

To decide whether there is sudden illumination change in the video frame, we make use of α^*_n. If the value of α^*_n is greater than the threshold value, then sudden illumination change is assumed, otherwise not. We determine α^*_n as below:

Let Θ_n be the area of unmoving region, and □$_n$ be the change in the intensity of unmoving region from the previous frame to the current frame. Here absolute value of □$_n$ is taken.

Therefore, $$\alpha^*_n = \frac{\delta_n}{\Theta_n} \quad (6)$$

To update the background frame, a weighted sum of the current background frame and instantaneous background is taken. The assigned weight determines the updation speed of the background frame. Therefore we calculated weight (α_n) adaptively and updates the background as follows:

$$\alpha_n = 0.9 \times \alpha_{n-1} + 0.1 \times \alpha^*_n; \quad (7)$$

$$B_C = \alpha_n \times IB_n + (1 - \alpha_n) \times B_C \quad (8)$$

α^*_n acts as a threshold for background updation.
So the background updation can be summarized as below:

if $(\alpha^{*}_{n} < \tau_h)$
$B_c = IB_n$
else
$\alpha_n = 0.9\times \alpha_{n-1}+0.1\times \alpha^{*}_{n}$;
$B_C = \alpha_n \times IB_n + (1- \alpha_n) \times B_C$
end if

τ_h is a threshold, determined experimentally.

Now this updated background can be used for the segmentation procedure of the moving vehicles. Because of the periodic update of the background frame, the segmented objects are now free from illumination and ghost of moving objects effect.

B. SHADOW REMOVAL

The methods of shadow detection and removal are mainly classified into two categories. The first category methods deals with detection and removal of static images where shadows are cast by static objects, whereas the second one deals with the shadows cast by moving objects. Here we are not interested in static shadows, because they are not detected as moving objects when using background subtraction, because they always have the same position over the successive frames and are not detected as segmented objects. We are interested in detecting and removing shadows which are cast by moving objects. Since the position of moving objects and their shadows keep on changing in successive frames, therefore the shadows are also detected as part of moving objects.

When using background subtraction, the shadows cast by moving objects are also detected as segmented objects. Presence of these shadows as segmented objects can distort the shape and geometrical properties of the objects. Therefore the removal of the shadows from the segmented objects becomes an inevitable task. So, the proposed shadow removal procedure is as below:

a) The chromaticity method proposed by Cucchiara et al.[8] is used to create a mask of the possible shadow pixels. Cucchiara has used the assumption that when a shadow is cast over an object, then there is only limited change in the hue and saturation value and resulting gray intensity is always less than the original intensity because of shadow casting, which is shown in Eq.(9). We set the threshold values low so that no shadow regions should be left to be considered as the candidate regions for further processing.

$$SP_n(x, y) = \begin{cases} 1, & if (\alpha \leq BRn(x, y) \leq \beta) and \\ & |SFn(x,y) - SBn(x, y)| \leq \tau s \; and \\ & |HFn(x, y) - HBn(x, y)| \leq \tau h \\ 0, & otherwise \end{cases} \quad (9)$$

BRn is the ratio of the intensity of current and background frame, SFn and SBn are the saturation values of current and background frame respectively, similarly HFn and HBn are the hue value of the current frame and background frame respectively.
α, β,τs,τh are the threshold values.

α gives the lower limit of how dark the shadow could be ,whereas value of β prevents the system to recognize foreground objects as shadows. , τs and τh determines the maximum allowable change in the saturation and hue values due to shadowing.

The value of τs and τh in our work is taken 0.55 and 75 respectively.
The pixels for which $SP_n = 1$, may belong to shadow pixels, otherwise they belong to foreground objects.

b) Each connected component corresponds to a candidate shadow region. For each pixel belonging to each candidate component in background and current frame, the gradient is calculated along horizontal as well as vertical direction:

$$|\nabla|_x = \frac{I(x+1,y) - I(x-1,y)}{2}$$
$$|\nabla|_y = \frac{I(x,y+1) - I(x,y-1)}{2}$$

where I(x, y) denotes the gray intensity of pixel (x, y). So the gradient magnitude is calculated as:

$$|\nabla|_{(x,y)} = \sqrt{|\nabla|_x^2 + |\nabla|_y^2} \quad (10)$$

c) For every candidate region, d_i calculates the change in the gradient value of each pixel between background frame and current frame. Then for each candidate shadow region, using d_i , we calculate K according to eq.(12).

$$d_i = \left||\nabla|_i^{bg} - |\nabla|_i^{fg}\right| \quad (11)$$

$$K = \left(\sum_{i=1}^{n} step(\eta - d_i)\right)/n; \quad (12)$$

where i=1…n (total no of pixels in the candidate region), and □ is a threshold value and step(x) function is given as:

$$step(x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & else \end{cases} \quad (13)$$

If value of d_i is more than threshold value, then at that pixel change in the intensity of background and current image is taken dissimilar.
K denotes the fraction of pixels having dissimilar change in intensity in background and foreground frame.
$if (K > \beta)$, then the component is a shadow region (14)
β is a threshold value, calculated experimentally.

e) From (14) we see that if value of K is greater than a threshold value, it means that a significant number of pixels belonging to candidate shadow region have a considerable change in the gradient value in foreground and background pixels. So, the candidate region is a shadow region and must be removed.

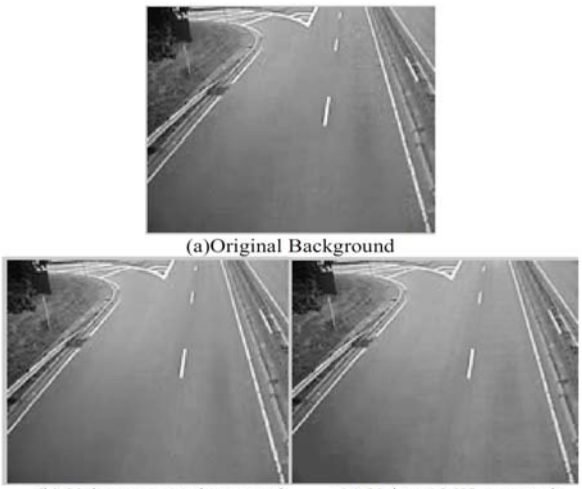
V. EXPERIMENTS

The simulations were run in MATLAB on a system with the following configurations:
1.) Intel core 2 duo processor with 1 GB RAM
2.) Windows 8 pro operating system.
Test is performed on videos from CAVALIAR dataset [13] and MATLAB Simulink.

Fig. 3 shows the adaptivity of background with the running frames. As we are periodically updating the background frame, we can see that the proposed method determines background nearly same as the actual background, while Adaptive Motion Histogram (AMH) [6] deviate somewhat from the original background.

Fig. 4 shows that the proposed approach is immune to sudden illumination change, while Gupte's et al. approach [5] falsely considers it as foreground object. It is because we have adaptively calculated value of α_n, therefore when there is sudden illumination change, then it takes less number of frames to adapt to the current background frame. But in Gupte's method value of α is taken constant (0.10), therefore it takes more number of frames to adapt to the current background, and considers background pixels as foreground.

Graph of Fig.5 shows that our approach is significantly faster tham AMH. This improvement in the speed is because of removal of unnecessary updation calculation. The other Graph shows that Gupte's [5] approach is giving sudden rise in the number of moving pixels, because it is considering sudden illumination change as foreground pixel, while our approach is resistant to this change.



(a)Original Background

(b) Using proposed approach (c) Using AMH approach

Fig.3: Effect of Background updation

(a)Original video frame (b) Updated background

(c) Using approach in [5] (d) Using proposed approach

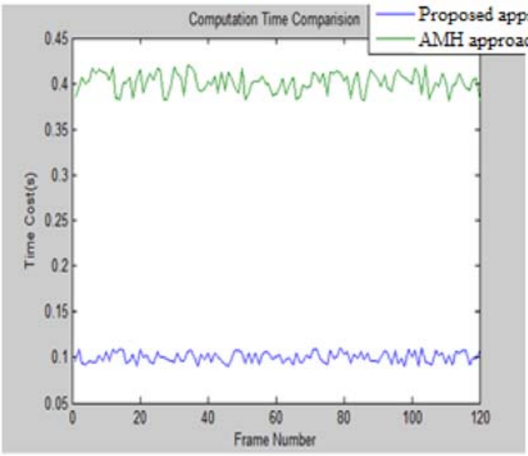
Fig.4: Effect of sudden illumination change on segmentation

Fig. 6 shows the results of shadow removal approach. We used black pixels to represent moving objects. Fig. 6(a) shows the original video frame. Fig. 6(b) shows that shadow is also detected as moving object. Fig. 6(c) shows the components of the moving objects which may belong to shadow regions. Fig. 5(d) shows the result obtained using proposed approach, which shows that it has successfully removed shadow regions from the detected moving objects.

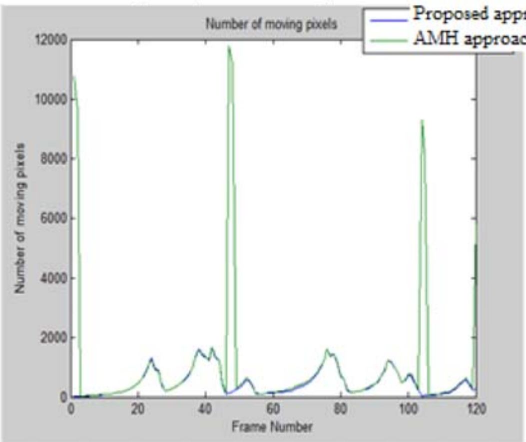
VI. CONCLUSION

This paper has presented background updation and shadows removal methods. Background subtraction method is commonly used for moving vehicle segmentation. But most of the methods based on this technique does not update background so as to conform to the changing environmental conditions. Therefore, in our work, background updation method has improved already existing method by intelligently updating background frame. Our method has avoided unnecessary updation operations, therefore making it possible to apply this algorithm in real time. This method is also resistant to ghost of moving objects effect and sudden illumination change.

In most of the methods, the segmented objects obtained after background subtraction method are directly fed to the subsequent processing operations, without considering about shadow removal. As these segmented objects may contain shadows falsely detected as moving objects, so it becomes imperative to remove the shadows. Our shadow removal method uses Cucchiara's [8] assumptions and uses gradient magnitude to perform further filtering and performs well by removing shadows from detected moving objects. This work can be even extended in the presence of dynamic background environments such as fluttering flags, swinging tree leaves etc.



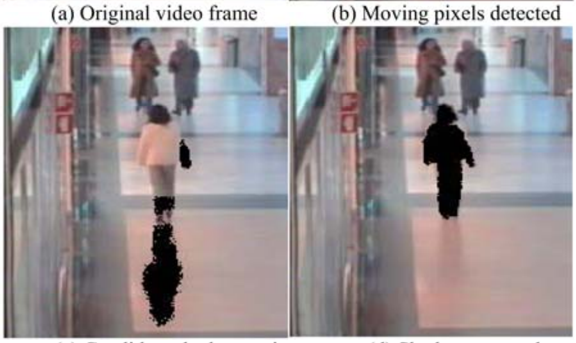
(a)Comparison of computation time



(b) Comparision of no of moving pixels detected

Fig. 5: Comparision of Computation time and no of moving pixels between proposed approach(blue) and Gupte's approach [5](green)

(a) Original video frame (b) Moving pixels detected



(c) Candidate shadow region (d) Shadow removal

Fig.6: Processing in proposed shadow removal method

REFERENCES

[1] C. Stauffer, W.E.L. Grimson, Adaptive background mixture models for real-time tracking, in: Proc. IEEE Int. Conference on Computer Vision and Pattern Recognition, vol. 2, 1999, pp. 246–252.J.

[2] S.J. McKenna, S. Jabri, Z. Duric, H. Wechsler, A. Rosenfeld, Tracking groups of people, Computer Vision Image Understanding 80 (1) (2000) 42–56.

[3] A.J. Lipton, H. Fujiyoshi, R.S. Patil, Moving target classification and tracking from real-time video, in: Proceedings IEEE Workshop on Applications of Computer Vision, Princeton, USA, 1998, pp. 8–14.

[4] D.Y. Huang, C.H. Chen, W.C. Hu, S.S. Su, Reliable Moving Vehicle Detection based on filtering of swinging tree leaves and raindrops, J. Vis. Commun. Image R. 23 (2012) 648-664.

[5] S. Gupte, O. Masoud, R.F.K. Martin, N.P. Papanikolopoulos, Transport. Syst. 3 (2002) 37–47

[6] W. Zhanga, Q.M.J. Wu, H. Yin, Moving vehicles detection based on adaptive motion histogram, Digital Signal Processing 20 (2010) 793-805.

[7] M.Seki, T.wada, H.Fujiwara, K.Sumi, Background subtraction based on cooccurance of image variations, 2003.

[8] R. Cucchiara, C. Grana, M. Piccardi, A. Prati, Detecting moving objects, ghosts and shadows in video streams, IEEE Transactions on Pattern Analysis Machine Intelligence 25 (10) (2003) 1337–1342.

[9] A. Sanin, C. Sanderson, B. C. Lovell, Improved Shadow Removal for Robust Person Tracking in Surveillance Scenarios, International Conference on Pattern Recognition, 2010.

[10] J.W. Heish, S.H. Yu, Y.S. Chen, and W.F. Hu. A shadow elimination method for vehicle analysis. In Pattern Recognition 2004. Proceedings of the 17th International Conference on, Volume 4, pages 372-375, Aug. 2004.

[11] A. Leone and C.Distante. Shadow Detection and moving objects based on texture analysis. Pattern Recognition, 40(4) (April 2007)1222-1233.

[12] N. Otsu, A threshold selection method from gray-level histograms, IEEE Trans. Syst. Man Cybernet. 9 (1979) 62–69.

[13] http://homepages.inf.ed.ac.uk/rbf /CAVIAR.