Real Time Shadow Removal with K-Means Clustering and RGB Color Model

Anuva Chowdhury and Ui-Pil Chong

School of Electrical Engineering, University of Ulsan, Ulsan, Korea
anuva_eeecuet@yahoo.com and upchong@ulsan.ac.kr

Abstract

This paper introduces a hybrid approach that is based on color information that utilizes a mask and K-Means clustering algorithm along with the frame averaging background subtraction technique. This hybrid approach efficiently removes artifacts caused by lightening changes such as highlight and reflection from segmentation, while also successfully removing shadows of stationary objects and dark cast shadows. Dark cast shadows cause an issue with tracking and detection. To eradicate these shadows, we first create a mask by assigning values to R, G and B channels utilizing the shadow properties to this RGB color individually, and then we apply K-Means clustering algorithm to this mask for efficient removal. Simulation results from several video sequences with different scene conditions also reveal the effectiveness and robustness of the proposed algorithm.

Keywords: *Background subtraction; K-means clustering; RGB color model; Shadow removal.*

1. Introduction

Detecting object in motion is the fundamental step for applications such as automated video surveillance, traffic monitoring, security system that require being robust against change in illumination conditions, which further causes large cast shadows, highlight, reflections of objects. To meet with these challenges, gradient filter is used to reduce the effect of shadows from the real time objects in [1], as shadow regions have small gradient value. Moreover, gradient domain is less sensitive to varying illumination conditions. In [2], an object-based methodology has been proposed to identify objects, ghosts and shadows in HSV (Hue, Saturation, Value) color space emphasizing the knowledge that, shadow pixels have similar chromaticity but lower intensity comparing with the background pixels. The frequency information of the shadow area is less than that of the other object's region. Based on this, shadow pixels can be removed by assigning appropriate threshold values as given in [3]. On the other hand, Gaussian mixture model (GMM) based approach is used to eliminate the shadow effects in [4], which is updated over time automatically. [5] implies to use shadow geometry to model and reduce shadow effects from automatic traffic surveillance system. Background subtraction method combining running Gaussian average filter with frame averaging process can also be used efficiently for removing shadows according to [6]. However, [7] suggests extracting two binary maps: one containing the foreground with shadow and the other containing some part of the foreground without shadow. A binary image is created from these two maps, and some inequality is being applied thereafter to the purpose of removing the shadow. The proposal of [8] is to use potential function to each pixel to find out the connectivity with the neighboring pixels. An object having sharp and irregular edges can contain a shadow without an edge as given in [9]. Using this information, cast shadow can be removed from real time environment. [10] proposes to use SVM classifier on color, texture and intensity characteristics to discriminate foreground pixels from shadow. In this paper, we propose a hybrid method which combines the intensity based K-Means clustering algorithm with the background subtraction technique described in [6] to remove artifacts like large cast shadows, global illumination and other lighting effects to make the real time detection process more robust and efficient against changing scene conditions.

2. Overview of Shadow Abolition

The lightning effects may cause redundancy in object tracking and as a consequence reduces system's accuracy. Thus we need to eliminate these luminance effects to make such systems reliable and practical against changing conditions. In our work, frame averaging process is used to remove bright lightening portions. After that, K-Means clustering with RGB color mask is used to minimize the remaining effects such as dark shadow portion and change in global illumination.

2.1. Background subtraction

The background and foreground are modeled by successively updating the average of the history of each pixel value for all pixel locations. The foreground is obtained by comparing the consecutive images and identifying the regions where they differ by using the following equation:

$$A_{t(R,G,B)} = |F_{t-1(R,G,B)} - F_{t(R,G,B)}| \tag{1}$$

where $F_{t(R,G,B)}$ is the current frame, $F_{t-1(R,G,B)}$ is the previous frame and $A_{t(R,G,B)}$ is the absolute difference image in the RGB color space.

The foreground mask is created as:

$$M_{t(R,G,B)}(x,y) = \begin{cases} 1, \text{ if } T_u < A_{t(R,G,B)}(x,y) < T_l \\ 0, \text{ otherwise} \end{cases} \tag{2}$$

where T_u and T_l are the upper and the lower thresholds, respectively.

2.2. Dark Cast Shadow Removal

2.2.1. Creation of RGB Color Mask: As we know that, shadow pixels are darker than the corresponding pixels in the background [11], assigning values on red, green and blue channels separately may reduce the intensity effects from the foreground objects. Thus the threshold values work as:

$$\sum_{n=1}^{3} M_n(x,y) = \begin{cases} 0, \text{if} Th_l < A_n(x,y) < Th_u \\ 1, \text{ otherwise} \end{cases} \tag{3}$$

where n is the number of channels, $M(x,y)$ is the mask image, $A(x,y)$ is the source image on which, threshold is being applied and Th_l and Th_u are the lower and upper threshold respectively, used to create the shadow mask.

2.2.2. Intensity Based K-Means Clustering: K-Means is an unsupervised clustering method used to classify the input pixels into several classes based on their inherent distance from each

$$J_{obj} = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \tag{4}$$

other. The pixels are clustered around the centroids obtained by minimizing the objective function, J_{obj}, which is calculated as follows:

where $\left\| x_i^{(j)} - c_j \right\|$ is the distance between the image pixels and the cluster centers , n is the number of pixels and k is the number of clusters.

The steps of this algorithm are given below:

Step 1: Compute the R, G and B intensities of the image based on the color mask created in the previous section.

Step 2: Initialize the centroids with k arbitrary intensities.

Step 3: Assign each pixel to the nearest cluster center.

Step 4: Relocate the centers in reception of new pixels and for clusters losing pixels. Repeat step 3 and step 4 until pixels do not change corresponding clusters any longer.

3. Proposed Algorithm

Step 1: First the original image is acquired in RGB format.

Step 2: Intermediate images are created to use them as references in background estimation and statistical analysis.

Step 3: The background is modeled by computing the mean and standard deviation of each pixel for 100 frames.

Step 4: The background is updated over time by using the running average filter with a learning rate, α. In this work, we have taken the value of α as 0.004, for better quality of the output.

$$D_{t+1(R,G,B)} = \alpha\, I_{t(R,G,B)} + (1-\alpha)\, D_{t(R,G,B)} \tag{5}$$

Step 5: Two thresholds are selected by the following manner:

$$\left.\begin{array}{l} \text{For upper threshold, } T_u\text{: } C(I) = A(I)+S \\ \text{For lower threshold, } T_l\text{: } C(I) = A(I)-S \end{array}\right\} \tag{6}$$

where C(I) is the threshold image, A(I) is the input image and S is the color value. The output threshold is just the addition or subtraction of a specific color value to each element of the source image. Here we have chosen the color value as 5.

Step 6: Now the extraction is carried out like this way, if T_u < pixel weight < T_l, the pixels are considered to be foreground instead of background.

Step 7: After foreground extraction, threshold values are applied on R, G and B channels separately to create shadow mask. Pixels closely related to the RGB mask are detected as shadow elements. The threshold values used for our work are as: (25<R<100), (20<G<140) and (B<=148).

Step 8: The remaining darkest shadow portions are removed by using the K-means clustering algorithm. The clusters centers are chosen between the original color and shadow portions. The number of clusters, iterations and the membership function are selected randomly based on the intensity mask. The clusters are created in a way that all shadow pixels belong to one cluster. By minimizing the objective function we get the actual shadow region. Now merging the centers of clusters characterizing the shadow region with those containing the background pixels, we can successfully remove the shadow effects from the moving objects.

Step 9: Finally morphological dilation is used to fillup the holes in the object information. A 3×3 kernel is used to get the required output.

4. Results and Discussions

In our experiment, three video sequences contain different information about object and shading, are employed for testing the performance of the proposed methodology and CAVIER data set is used to evaluate the visual performance of background subtraction technique [6]. The collected videos are preconditioned as:

1) We assume that the background and the camera remain still during the process.

2) No sudden changes in illumination occur during background estimation.

3) Image Processing has been carried out on the video sequences and then images are extracted from simulation results.

The evaluation is performed in two ways, one is the qualitative measurement and another is the quantitative measurement. For these, our method is compared with the method described in [6]. Both of these algorithms have been implemented in the C++ environment using OpenCV library.

Figure 1 depicts that frame averaging background subtraction technique can efficiently detect objects when there is no significant change in illumination occur. It also can remove the shading and small reflection portion of objects efficiently. There are no difficulties in taking out multiple moving objects by using the background subtraction technique as in [6].

Browse 1	EnterExitCrossing Path2cor	LeftBag

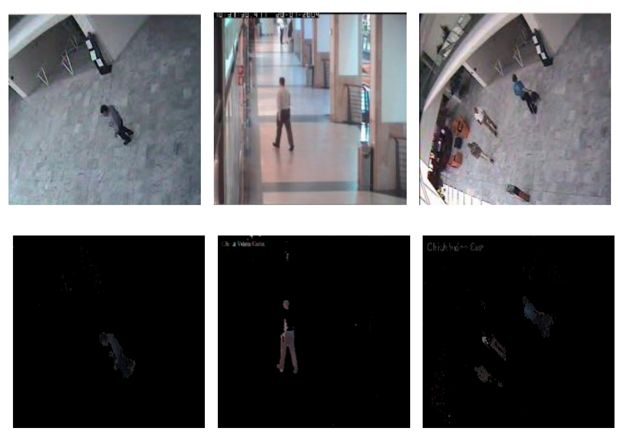

Figure 1. Simulation Results of Background Subtraction Described [6]

Figure 2 illustrates the visual representation of the proposed detection methodology. As it is seen that the background subtraction technique fails to distinguish the moving object from its dark cast shadow whereas the proposed methodology successfully detects the object and segments the shadow as background.

Three matrices are employed to evaluate the quantitative performance of the real time object detection algorithm: the Detection Rate (DR), the Specificity (Spec) and the False Alarm Rate (FAR). Ground truth is prepared manually over five frames for each sequence representing different lighting conditions and perspectives. The results are given in table 1 which also illustrates the superior performance of the proposed hybrid methodology for all

$$\left.\begin{aligned} DR &= \frac{TP}{TP+FN} \\ Spec &= \frac{TN}{TN+FP} \\ FAR &= \frac{FP}{FP+TP} \end{aligned}\right\} \quad (7)$$

cases and thus approves the perspective representation of the segmentation.

Table 1: Quantitative comparison of [6] and the proposed method

Videos / Matrices	Fire3			Sneak-Walk			IK-Pole		
	DR%	Spec%	FAR%	DR%	Spec%	FAR%	DR%	Spec%	FAR%
Method in [6]	84	58	83	82	98	17.7	73	99	33
Proposed method	84.3	90	15	84	99	23	79	99	14

Proposed hybrid

Method in [6]

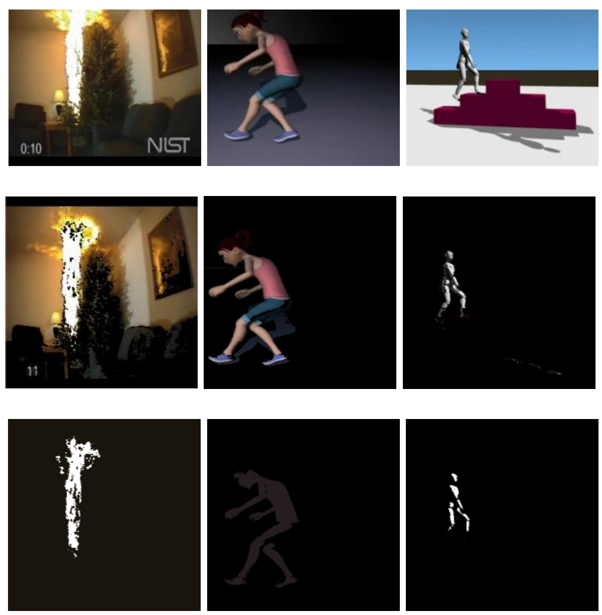

Figure 2. Visual comparison of [6] and our approach.

To evaluate the real time performance, we have checked the frame rate. According to our experiment, the total execution time including the whole output streams took 9 second to process 100 frames for each video sequence on an Intel Core i5 CPU 2.81 GHz, 3.49 GB of RAM system which is approximately 11 fps.

5. Conclusions

In this paper, we proposed a hybrid system to remove shadow from moving object for a real time system. The hybrid system first uses frame averaging background subtraction technique with running Gaussian averaging filter to remove artifacts such as objects highlight, small bright cast shadow. To pull out the large dark cast shadow from the foreground, we utilize the shadow characteristics to RGB color model and apply K-Means clustering algorithm, which partitions the shadow portion from the object region. Experimental results also demonstrate the superiority of the proposed method in real time shadow removal and object detection to changing conditions. The accuracy of this algorithm reduces for dynamic background and abrupt change in illumination occur. Those facts will be considered in future to make this algorithm more adaptable and reliable with changing conditions.

Acknowledgements

The research is funded by the School of Electrical Engineering in excellence program at University of Ulsan, 2012.

References

[1] C. Shao-Yi, M. Shyh-Yih and C. Liang-Gee, "Efficient Moving Object Segmentation Algorithm Using Background Registration Technique", IEEE Transactions on Circuits and Systems for Video Technology, 12, 7, pp. 577-586, **(2002)**.

[2] R. Cucchiara, C. Grana, M. Piccardi and A. Prati , "Detecting Moving Objects, Ghosts and Shadows in Video Streams", IEEE Transactions on Pattern Analysis and Machine Intelligence, 25, 10, pp. 1337-1342, **(2003)**.

[3] H. Ching-Tang, E. Lai, W. Yeh-Kuang and L. Chih-Kai, "Robust, Real Time People Tracking with Shadow Removal in Open Environment", 5th Asian Control Conference, pp. 901-905, **(2004)**.

[4] N. Martel-Brisson and A. Zaccarin, "Moving cast shadow detection from a Gaussian mixture shadow model", in Proc. IEEE Conf. Comput Vision Pattern Recog., pp. 643-648, **(2005)**.

[5] H. Jun-Wei, Y. Shih-Hao and C. Yung-Sheng, "Automatic Traffic Surveillance System for Vehicle Tracking and Classification", IEEE Transactions on Intelligent Transportation Systems, 7, 2, pp. 175-187, **(2006)**.

[6] Z. Tang, Z. Miao and Y. Wan, "Background Subtraction Using Running Gaussian Average and Frame Difference", IFIP International Federation for Information Processing, **(2007)**.

[7] M. Izadi and P. Saeedi, "Robust Region-Based Background Subtraction and Shadow Removing Using Color and Gradient Information", Proceedings of the 19th International Conference on Pattern Recognition ICPR, pp. 1-5, IEEE Press **(2008)**.

[8] Y. Wang, "Real-Time Moving Vehicle Detection with Cast Shadow Removal In Video Based on Conditional Random Field", IEEE Transactions on Circuits And Systems For Video Technology, 19, 3, pp. 437-441, **(2009)**.

[9] S. Lakshmi and V. Sankaranarayanan, "Detecting Moving Objects From Dynamic Background With Shadow Removal", Trendz in information science and computing(TISC), 19, 3, pp. 245—247, IEEE Press, Chennai **(2010)**.

[10] W. Shih-Chieh, S. Te-Feng and L. Shang-Hong, "Detecting Moving Objects From Dynamic Background With Shadow Removal. IEEE International Conference on Acoustic, Speech and Signal Processing (ICASSP), pp. 925-928, IEEE Press, Taiwan **(2011)**.

[11] D. Grest, J. M. Frahm and R. Koch, "A Color Similarity Measure for Robust Shadow Removal in Real-Time", Proceedings of the Vision, Modeling, and Visualization Conference 2003 (VMV 2003), Germany **(2003)**.