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Background Subtraction for Object Detection under Varying Environments

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***Abstract*: Background subtraction is widely used for extracting unusual motion of object of interest in video sequences for various applications. In this paper, we propose a fast and flexible approach of object detection based on an adaptive background subtraction technique which also effectively eliminates shadows based on color constancy principle in RGB color space. This approach can be used for both outdoor and indoor environments. Our proposed method of background subtraction makes use of multiple thresholding technique for detecting object of interests for any given scene. Once the moving object has been detected from the complex background, then the shadows are detected and eliminated by considering some environmental parameters.**

***Keywords*:** background subtraction, object detection, shadow removal, multiple thresholding, indoor and outdoor environment

I. Introduction

The detection of unusual motion is the ultimate goal in any surveillance system. This goal is achieved when the system has very low false detection rate. The task of automatic object detection is highly regarded for a variety of applications including video surveillance [1], remote sensing [2], crack detection in concrete pipe [3], under water object detection [4] and driver assistance systems [5].

One of the most common approaches in detecting and tracking targets in real time video applications is the temporal differencing (TD) technique [6]. In this approach, video frames are separated by a constant time δt and compared to find regions which have changed. While this technique is fast, it has limitations. For instance, tracking is impossible if there is major camera motion, unless a proper image stabilization technique is employed. This approach also fails if the object becomes obstructed or terminates its motion. Template correlation matching is another approach that falls into the temporal differencing approach. The drawback of this approach is that it requires that the object of interest's appearance remains persistent and thus, it is not robust to changes in object size, orientation or even changes in the lighting conditions. There are many variants on the TD method but the easiest is to take consecutive video frames and define the absolute variance. A threshold function is then used to determine the change.

Other common methods are optical flow [7] and background subtraction [8] techniques. Two-dimensional (2D) image motion is the projection of the three-dimensional (3D) motion of targets from the world coordinates to the corresponding image plane [9]. Arrangements of time-oriented captured images allow the assessment of the projected 2D image motion as discrete image displacements which are called the optical flow field or the image velocity field. Optical flow method has been used in motion recognition, object segmentation, time-to-collision and focus of expansion calculations, motion compensated encoding, and stereo disparity measurement [9]. In real world scenes, however, especially in the outdoor scenes, this restriction, i.e., stationary background often turns out to be impractical because the background scenes are not stable. In addition, optical flow technique is computationally costly and is inapplicable to real-time algorithms without specialized hardware [10].

Background subtraction is a suitable method for detecting and recognizing foreground objects in the static background, [11]. Background subtraction method depends on environmental conditions. Two important criteria are:

1) Dependency on illumination changes and unessential events, and 2) Dependency on background objects motion.

In order to carry out foreground object detection and recognition even in a dynamic environment, two types of methods have been proposed: 1) using the motionless background model with an acceptable range of image differences at each pixel or local image area, and 2) using dynamically updated background model.

Most of the methods under the first type set a permissible range according to the formulation of background variations (e.g., illumination variations) [12, 13], or according to the statistical analysis of training samples of background images [14, 15]. A proper threshold value should be set so that, when a pixel value or local image pattern is mapped outside or greater than of this value, it is detected as a foreground object or labeled as a background otherwise. As a result, the detection sensitivity decreases for those pixels have a wide range of

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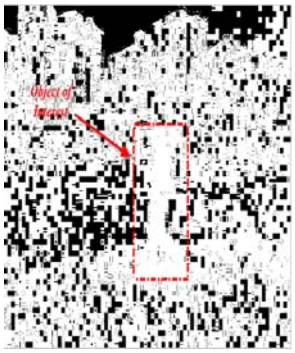
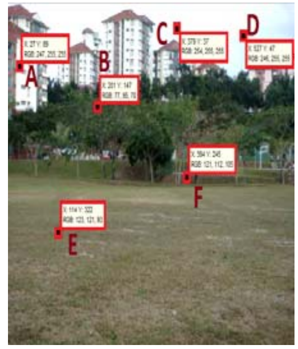
(a) Reference Frame (RF)

(b) Sample Frame (SF)



(c) After background subtraction (pixel to pixel)

Figure 1. Background subtraction without environmental considerations. (a) shows the reference frame, (b) shows the sample frame, and (c)shows background subtraction results.



(a) RF the 30th frame

(b) SF the 60th frame

Figure 2. Green background scene. (a) Reference frame taken at 30th frame, (b) Sample frame taken at 60th frame.

possibility. This issue can be overcome by extending the feature space dimension. However, this is not practical since this approach needs many background images for training and modeling the high-dimensional space. Existing background subtraction methods may require additional algorithms to overcome outliers or unwanted moving objects. For example, in the case of forest fire detection, the goal is to differentiate between the fire and the rest of the background. In this case, possible outlier could be movement of leaves or movement of animals whose skin color has some similarity to the color of fire. To solve such variation of patterns in the color or shapes, technique such as monitoring and tracking the area of concerned overtime has been suggested. In this case special filters and training method to recognize fire as the object of interest would be applied [16].This process is usually time-consuming and complicated. Then, there is another problem of shadow. Shadow is another challenging problem in object detection and recognition as it contributes to error.

The method proposed in this paper is a robust background subtraction method for various illumination and motion conditions. This method has been developed to work for both indoor and outdoor scenes. The technique consists of two kinds of operation, one for removing the stationary background and the other is for removing shadows. Each operation consists of several components that take into account some environmental conditions. This paper is organized as follows: section two describes a technique for outdoor environment while section three tackles the indoor environment.

In this section also a technique for shadow removal under indoor conditions is provided. Experimental results are presented in section four. Section five provides some ongoing and future works and finally section six concludes this paper.

II. Outdoor environments

An example of outdoor moving object is shown in Fig. 1 which consists of a reference (RF) and a sample (SF) frame (Fig. 1a and 1b respectively). Outdoor scene usually involves many small unwanted moving objects. Hence, direct intensity pixel by pixel background subtraction is not recommended. Implementing background subtraction in such a brute-force method which converts the color image from RGB color format to Gray level format and then show the result in a binary representation could result in many useful information being missed and at the same time many unwanted outliers being detected. This scenario is illustrated in Fig. 1c where the result of background subtraction is shown without considering environmental conditions such as variation in the sky illumination or wind.

Without loss of generality, let’s assume that camera is looking into a park or in the area which is covered by trees or grass as shown in Fig. 2. Changes in position of leaves and bushes due to any external forces such as wind will lead to a false detection of a new object in the extreme case, or produce lots of noise spots in a less extreme case. These problems can also occur when there are changes in the illumination. In this case, we will see different intensity values in the affected region between the RF, Fig. 2a, and SF, Fig. 2b, as indicated in Fig. 2.After analyzing nearly 1000 video sequences, it has been found that intensity fluctuations for each Red, Green and Blue channels differ most of the time.

Table I shows changing of intensity values for a number of points indicated in Fig. 2a and Fig. 2b. The marked points in this figure belong to two different categories, the sky areas (A, C, and D) and the green areas (B, E, and F). As an example, consider point E which is located in the green area. The values of the RGB channels in RF changed from 123, 121, 93 respectively to 126, 124, 94 respectively although the mixture of the three colors still remains brownish green because of little change in luminance within 30 frames. However, looking at point D (sky area), the value for Red any pixel in SF belongs to the background where its difference from the corresponding pixel in RF does not exceed the critical values. From our experiment and analysis channel has changed drastically while values for Green and background subtraction mechanism be

Table I, Pixel values fluctuation based of RGB channels

Number	Intensity value of specific pixels in 30th frame			Intensity value of specific pixels in 60th frame		
Color	R	G	B	R	G	B
A	247	255	255	249	255	255
B	77	95	70	90	109	93
C	254	255	255	253	255	255
D	246	255	255	205	255	255
E	123	121	93	126	124	94
F	121	112	105	171	188	213

performed on each of the RGB channels between the RF and SF. We propose that Blue channels maintained. Because of this, we propose the of almost 1000 video sequence, we found that in more than 90% of the cases the critical values stay within the range from ±29 to ±32. However, these ranges are not suitable for sky areas or, in generally, bright areas. The pseudo code for this green area removal is given below.

For i=1 to Image_Height

For j=1 to Image_Width

If $(R^{RF}_{ij} -29 < R^{SF}_{ij} < R^{RF}_{ij}+29)$ AND

$(G^{RF}_{ij} -29 < G^{SF}_{ij} < G^{RF}_{ij}+29)$ AND

$(B^{RF}_{ij} -29 < B^{SF}_{ij} < B^{RF}_{ij}+29)$

Then

P^{SF}_{ij} belongs to back ground

Set

$P^{SF}(i, j, R) = 0;$

$P^{SF}(i, j, G) = 0;$

$P^{SF}(i, j, B) = 0;$

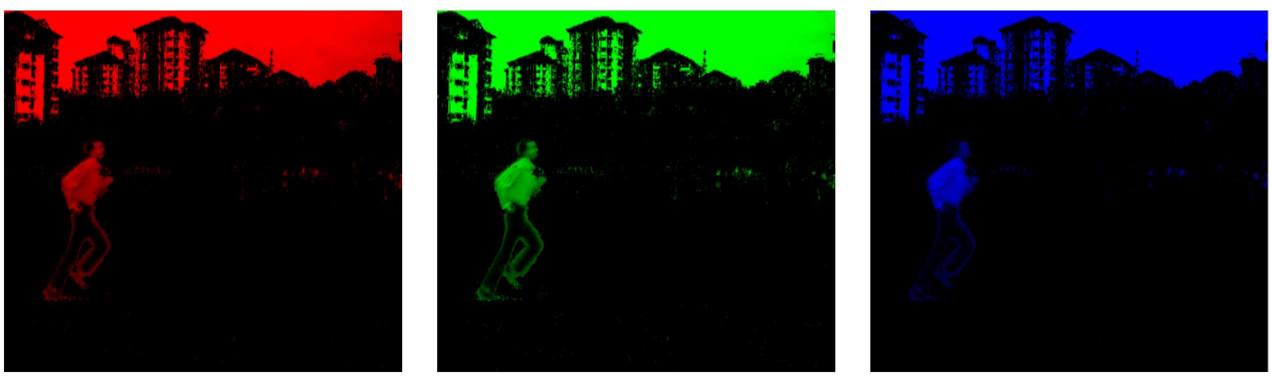
End

End

End

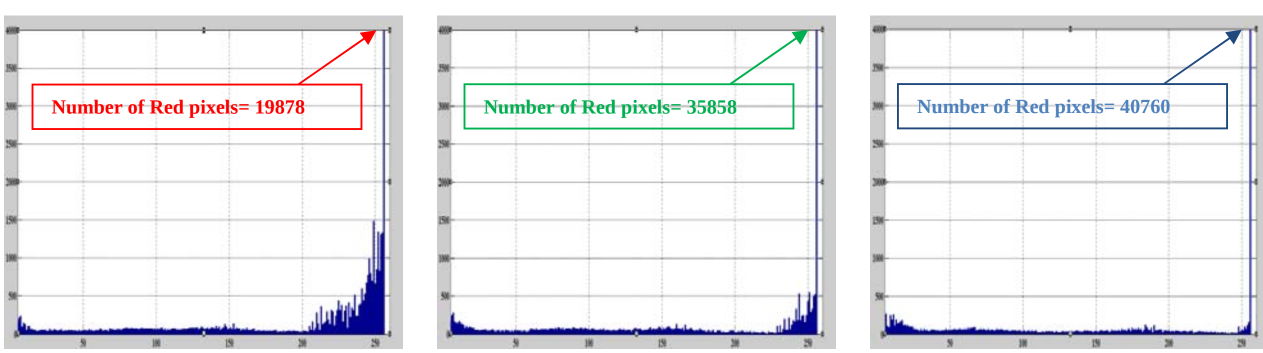
Note: $P^{SF}(i,j,C)$ stands for the sample frame pixel values at position (i,j) and C is the color component either red, green, or blue.

Besides, Fig. 3 shows the result of such removal. Figure 3a is the SF with respect to RF in Fig. 2a while Fig. 3b presents the results of employing the operation for removing stationary background (green area). To remove the sky area, the histogram for each channel after the green area is removed is analyzed. Figure 4 shows the histogram for Fig. 3 for each of the three channels. From the resulting histograms (see Fig. 5), we found that the sky area constitutes all pixel values above 190. Hence, by classifying all pixels above 190 for each of the three channels as the sky region, we can remove this sky region



(a) Red channel (b) Green channel (c) Blue channel

Figure 3. Resulting image in respective channels (4a) Red, (4b) Green, (4c) Blue.



(a) Histogram for Red channel (b) Histogram for Green channel (c) Histogram for Blue channel

Figure 4. Resulting histograms in respective channels (a) Red, (b) Green, (c) Blue.

(a) SF (b) After removal of green area

Figure 5. Green background removal (a) Before the removal, (b) after the removal.

Figure 6. SF after implementing the sky removalalgorithm

Figure 7. SF after implementing Median Filter

from the SF. Figure 6 shows the result for this sky removal is given below.

We noted that there are still some spurious noises present in the image, but this can easily be removed by applying a median filter. This is shown in Fig. 7. We also noted that the reference background needs to be updated from time to time especially if the monitoring is from morning to evening. Any of the available method for updating the background can then be applied. Then, the next stage is to tackle the shadow problem. We defer our discussion on this shadow removal in the indoor environment background subtraction section. Figure 8 illustrates procedure of implementing the operations on removing both the green and the sky area.

The pseudo code for this sky removal is given below.

For i=1 to Image_Height

For *j*=1 to Image_Width

If 190 < R^{SF}_{ij}AND

190 < G^{SF}_{ij} AND

190 < B^{SF}_{ij}

Then

P^{SF}_{ij}belongs to sky

So

$P^{SF}(i, j, R) = 0;$

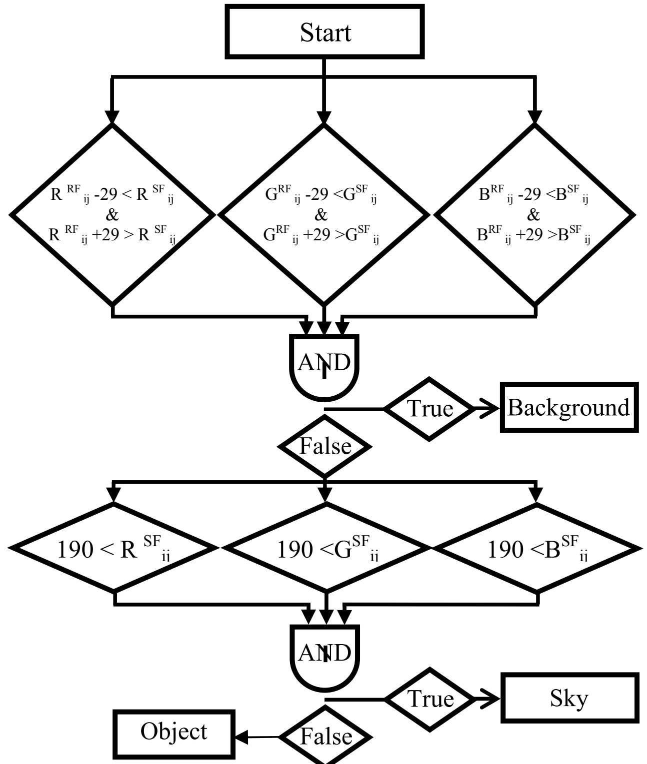


Figure 8. Flowchart for removing background in outdoor scenes

$P^{SF}(i, j, G) = 0;$

$P^{SF}(i, j, B) = 0;$

End

End

End

III. Indoor environments

In the indoor environment, moving object misclassification due to shadow is one of the major problems. In general, shadows are of two classes: self and cast shadows. A self-shadow occurs in the portion of an object which is not illuminated by direct light. A cast shadow on the other hand is the area projected by the object in the direction of direct light [17]. There have been many approaches proposed to tackle this problem. In one work reported by Chien et. al.,once the difference between two consecutive frames is computed and thresholded, the spatial and temporal information is applied to tune the boundary, hence the rough location and shape of objects can be detected [18]. In another approach by Fuyuan et. al., the background is modeled and adaptively updated in Hue Saturation Intensity (HSI) color space. Detection errors are dealt with motion continuity and velocity consistency. Finally, cast shadows are removed by the generic properties of luminance, chrominance and gradient density [19].

After analyzing many indoor video frames, we found that light reflection from the wall and cast shadow are two important problems. To overcome these problems and therefore to be able to detect the object of interest correctly, we proposed multi-thresholding technique to every frame.

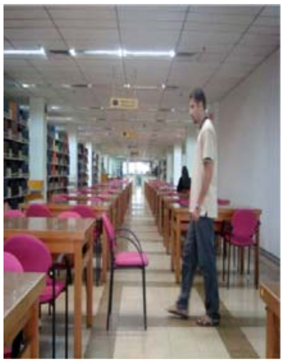


Figure 9. SF in the indoor area

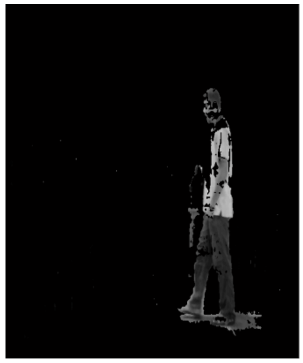


Figure 10. Result after subtraction

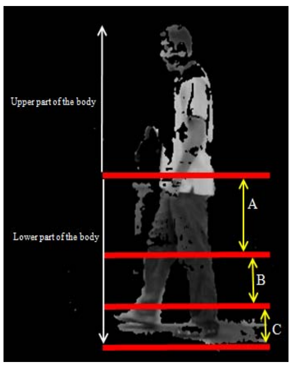


Figure 11. Separate subregions for lower Mid-Shape region

Figure 12. Final result

Figure 9 shows an example of person walking in a library and Fig. 10 shows the result of using the proposed background subtraction technique. As can be seen, the shadow appears in the lower part of the body because in most cases the light sources are placed either on the ceiling or on the wall. To remove shadows attached to bottom part of the object, the first step is to find the middle position of the object of interest for every frame. These can be achieved using equation (3).

$$\text{Mid\_Shape}(Y) = \frac{\text{Min}(y) + \text{Max}(y)}{2} \quad (1)$$

$$\text{Mid\_Shape}(X) = \frac{\text{Min}(x) + \text{Max}(x)}{2} \quad (2)$$

$$\text{Mid\_Shape} = (\text{Mid\_Shape}(X), \text{Mid\_Shape}(Y)) \quad (3)$$

Using this position, the object of interest is divided into two parts: upper Mid-Shape region and lower Mid-Shape region. The upper region is thresholded using similar algorithm as for the outdoor environment. For the lower region, it is further divided into three sub regions labeled as A, B and C as shown in Fig. 11. For each part, a different threshold value is used. It is worth noted here that the area close to the ground normally has more effect on the self and cast shadow. Thus, the threshold value for this area C should be greater than the other two areas. From our experiments, region A is defined as all pixels lie in between the Mid-Shape horizontal line and 2/3 of the Mid-Shape line (with respect to the ground), likewise region B is defined as all pixels lie in between 2/3 of the Mid-Shape line and 1/6 of the Mid-Shape line, and finally region C is for all pixels in between 1/6 of the Mid-Shape line and ground (Note: ground line is the lowest value of Y coordinates of the detected object– see Fig. 11), Fig. 12 shows how the shadow of the moving object mainly in sub regions B and C has been removed. Based on the experiments in cases which a group of people are located together, object is small due to being far from camera, or the positions of light sources are located oriented respect to the object of interest and near that dividing lower region of Mid-Shape in to five parts is useful. Therefore, the maximum value of thresholded for sub regions A, B, C, D, and E is 65 (for sub region E) and the minimum value is 33 (for sub region A). We set up our divisions as part A from Mid-Shape horizontal line and 3/10 of the Mid-Shape line, B from 3/10 Mid-Shape and 6/10 of the Mid-Shape, C from 6/10 Mid-Shape and 8/10 of the Mid-Shape, D from 8/10 Mid-Shape and 9/10 of the Mid-Shape, E the rest of object.

The Pseudo code for multiple thresholds is presented as follow:

Subregion A: Mid_Shape to (2× Mid_Shape)/3
Subregion B: (2× Mid_Shape)/3 to Mid_Shape/6
Subregion C: Mid_Shape/6 to ground

Find the Mid-Shape
Divide the lower part into three regions
If points belong to the above of the Mid-Shape
  Then Use normal threshold
Else
  If points belong to sub region A
    If $(R^{RF}_{ij} - 33 < R^{SF}_{ij} < R^{RF}_{ij} + 33)$ AND
      $(G^{RF}_{ij} - 33 < G^{SF}_{ij} < G^{RF}_{ij} + 33)$ AND
      $(B^{RF}_{ij} - 33 < B^{SF}_{ij} < B^{RF}_{ij} + 33)$ then
      P^{SF}_{ij} belongs to background thus set
      $P^{SF}(i, j, R) = 0;$
      $P^{SF}(i, j, G) = 0;$
      $P^{SF}(i, j, B) = 0;$
    End
  End
  If points belong to sub region B
    If $(R^{RF}_{ij} - 45 < R^{SF}_{ij} < R^{RF}_{ij} + 45)$ AND
      $(G^{RF}_{ij} - 45 < G^{SF}_{ij} < G^{RF}_{ij} + 45)$ AND
      $(B^{RF}_{ij} - 45 < B^{SF}_{ij} < B^{RF}_{ij} + 45)$ then
      P^{SF}_{ij} belongs to background,
    End
  End
  If points belong to sub region C
    If $(R^{RF}_{ij} – 65 < R^{SF}_{ij} < R^{RF}_{ij} + 65)$ AND
      $(G^{RF}_{ij} – 65 < G^{SF}_{ij} < G^{RF}_{ij} + 65)$ AND
      $(B^{RF}_{ij} – 65 < B^{SF}_{ij} < B^{RF}_{ij} + 65)$ then
      P^{SF}_{ij} belongs to background
    End
  End
End

IV. Experimental results

This section presents results of applying the proposed methods onto different scenes with different backgrounds. In Fig. 13a, an infrared VGA CCTV camera was used for the security purpose and the detected object is shown in Fig. 13b (the object is also been zoomed in). The implementation of the "green" area and sky area removal algorithms successfully detected the moving object. Median filter was further applied to clean up the result as shown in Fig. 13b. Fig. 14a shows an outdoor environment taken also by an infrared camera in which object of interest located in 15meters far from the camera which is installed at the top of building. Figure14b shows the result of applying the proposed method. Besides, Fig. 14b illustrates this technique works fine in situations which object of interest is so small or becomes small due to a far distance from camera. Fig. 15a shows a similar scene as in Fig. 13 except that the camera used was the normal VGA CCTV camera. Note the presence of a strong shadow of the moving person because of light sources and reflection of light from floor. Fig. 15b shows that our proposed method not only able to detect the desired moving object but also able to remove the shadow of the person. Figure 16 shows another capability of our method. In this scene, a camouflaged soldier is not easily detected by the human eyes. Nevertheless, our method is still able to detect the moving soldier free of any dependency on texture based algorithm, [20]. Despite the methods are just configured for removing background under the mixture of varying illuminations [21 and 22], Fig. 13 and 15 as well as 16 illustrate that this method can overcome on the problem of changing in illumination in the scene and is able to eliminate shadows after removing background without complicated mathematic algorithm. Figure 17a shows the detection of multiple people walking together while camera is installed at a higher level and is located far from the objects. Fig.17b present results of the outdoor background subtraction. Figure 17 shows position of camera doesn't have effect on the result as long as its position doesn't cause loss of Mid-point. Figure 18 illustrates another potential application of our proposed method. In this scene, infrared camera is being used to detect a wild animal. Fig. 18b clearly shows that the animal has been completely detected. The proposed method also is suitable for military applications. Fig. 19 shows a fighter jet that has been detected behind an open sky. From the result (as shown in Fig. 19b), a complete silhouette of the aircraft has been obtained. This could be very useful for accurate classification or identification stage. Finally, we also show the capability of our algorithm in detecting fire or flame as illustrated in Fig. 20. All of the above tests were conducted using Intel core 2 Duo processor running on a 2.26 GHz with 2GB above RAM machine. All images are set to the normal VGA video size. In terms of the computation speed, we measure that for all of the images, the computation speed is in the range between 0.05 and 0.072 seconds. This processing time can be considered slow due the scanning mechanism from left to right and top to bottom of the entire frame. To alleviate this problem, the proposed technique should be applied only onto the region of interest (ROI). This will then ensure that the processing time will be less than 40 milli-seconds for a real-time video processing.

Figure. 13a. Indoor infrared moving person

Figure. 13b. Zoomed in result for indoor moving person

Figure. 14a. Outdoor infrared moving person

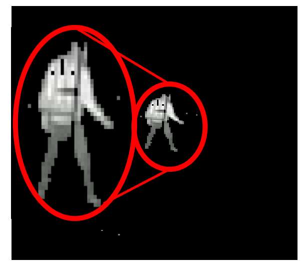


Figure. 14b. Zoomed in result for outdoor moving person

Figure. 15a. Indoor VGA CCTV containing moving person

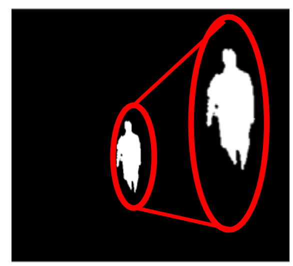


Figure. 15b. Zoomed in result for indoor VGA CCTV

Figure. 16a. Outdoor RF

Figure. 16b. Camouflaged solder in SF

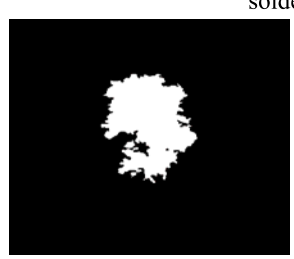


Figure. 16c. Result of object detection (the object is also been zoomed in)

V. Future work and recommendation

There are many works we need to do further and these are given as follows:

1. Elimination of combined or overlapped shadows of two or more objects.
2. Elimination of cast shadow appeared on walls.
3. While camera is installed vertically and there are horizontally light sources, this method is not suitable because of missing Mid-point of object of interest. Hence, to compensate this difficulty there is another opportunity for further work.

VI. Conclusion

This paper has provided an alternative method to detect moving objects using background subtraction framework. The strength of this technique is that it is robust against non-salient motion (such as moving leaves) with the presence of shadows. In order to prove our claim, we have demonstrated the proposed method for different video sequence. The main contribution towards the success of the detection in our method is that we employed multiple thresholding mechanism in our algorithm.

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References

[1] R. Collins, A. Lipton, and T. Kanade, “Introduction to the special section on video surveillance,” IEEE Trans. Pattern Anal. Mach. Intell., Aug. 2000, vol. 22,no. 8, pp. 745–746.

[2] L. Bruzzone and D. F. Prieto, “An adaptive semiparametric and context-based approach to unsupervised change detection in multitemporal remote-sensing images,” IEEE Trans. Image Processing, Apr. 2002, vol. 11, no. 4, pp. 452–466.

[3] Sunil K. Sinha and Paul W. Fieguth, “Automated detection of cracks in buried concrete pipe images” Elsevier B.V, 2005.

[4] GL Foresti and S Gentili, “A vision based system for object detection in underwater images,” International Journal of Pattern Recognition and Artificial Intelligence (IJPRAI), 2010.

[5] C.-Y. Fang, S.-W. Chen, and C.-S. Fuh, “Automatic change detection of driving environments in a vision-based driver assistance system,” IEEE Trans. Neural Netw. , May 2003, vol. 14, no. 3, pp. 646–657.

[6] C.Anderson, P.Burt, G. van der Wal. “Change detection and tracking using pyramid transformation techniques,” SPIE – Intelligent Robots and Computer Vision,1985, VOL. 579, pp. 72-78.

[7] J Shin, S Kim, et all, “Optical flow-based real-time object tracking using non-prior training active feature model” Computer Vision and Image Understanding, June 2005, Volume 98, Issue 3, Pages 462-490.

[8] B.Hosseini, Saeed Vahabi Mashak and A.S.R Abu Bakar, “Human Movement Based on Rule based Classifier" Asia Modelling Symposium, May 2010.

[9] [14] S.S. Beauchemin and J.L. Barron, “The Computation of Optical Flow”, ACM Computing Surveys, 1995 Vol. 27,No.3, PP 43-467.

Figure. 17a Multiple objects in SF

Figure. 17b Result of multiple objects detection

Figure. 18a Reference frame using IR camera

Figure. 18b Sample frame with moving animal

Figure. 18c. Result of object detection

Figure. 19a An aircraft t in the sky

Figure. 19b Result of object detection

Figure. 20a Outdoor reference frame

Figure. 20b An explosion in a sample frame

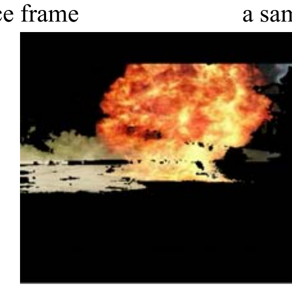

Figure. 20c Result of object detection

[10] H Fujiyoshi, Alan.J Lipton and Takeo Kanade, "Real-Time Human Motion Analysis by Image Skeletonization" IEICE TRANS.INF. & SYST, JANUARY 2004, VOL.E87-D, NO.1.

[11] Makito Seki, Toshikazu Wada, Hideto Fujiwara, Kazuhiko Sumi, "Background Subtraction based on Cooccurrence of Image Variations" Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'03) , IEEE, 2003.

[12] N. M. Oliver, B. Rosario, A. P. Pentland, "A Bayesian Computer Vision System for Modeling Human Interactions," IEEE Trans. on PAMI, 2000, Vol.22, No.8, pp.831-843.

[13] T. Matsuyama, H. Habe, R. Yumiba, K. Tanahashi, "Background Subtraction under Varying Illumination," Proc. Of 3rd Int'l Workshop on Cooperative Distributed Vision, 1999, pp.225-246.

[14] I. Haritaoglu, D. Harwood, L. S. Davis, "A Fast Background Scene Modeling and Maintenance for Outdoor Surveillance," Proc. of ICPR, 2000, Vol.4, pp.179-183.

[15] M. Seki, H. Fujiwara, K. Sumi, "A Robust Background Subtraction Method for Changing Background," Proc. of IEEE Workshop on Applications of Computer Vision, 2000, pp.207-213.

[16] Li Ma, Kaihua Wu,L. Zhu, "Fire smoke detection in video images Using Kalman filter and Gaussian Mixture Color model", International Conference on Artificial Intelligence and Computational Intelligence, 2010, Page 484.

[17] Li Xu, Feihu Qi, Renjie Jiang, Yunfeng Hao, Guorong Wu, "Shadow Detection and Removal in Real Images: A Survey" Shanghai JiaoTong University, P.R. China, June 2006.

[18] S.Y. Chien, S.Y. Ma and L.G. Chen ," Efficient moving object segmentation algorithm using background registration technique" IEEE Trans Circuits Syst. Video Technol, JULY 2002, pp. 577–585.

[19] Hu Fuyuan, Zhang Yanning, et all, "A New Method of Moving Object Detection and Shadow Removal" JOURNAL OF ELECTRONICS (CHINA), July 2007, Volume 24, Number 4, 528-536.

[20] Dongxiang Zhou, Hong Zhang and Nilanjan Ray,"Texture Based Background Subtraction", Proceedings of the International Conference on Information and Automation, Zhangjiajie China, IEEE Conference, June 20 -23, 2008.

[21] Yunlong Guo, Bo Yang, Yangyang Ming, Aidong Men, "An Effective Background Subtraction Under the Mixture of Multiple Varying Illuminations",Second International Conference on Computer Modeling and Simulation, IEEE Conference, 2010.

[22] Makito Seki, Hideto Fujiwara, Kazuhiko Sumi, "A Robust Background Subtraction Method for Changing Background", Applications of Computer Vision, Fifth IEEE Workshop. 2000.

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