Yugoslav Journal of Operations Research
14 (2004), Number 1, 117-132

NEW ALGORITHM FOR MOVING OBJECT DETECTION

Vesna ZELJKOVIĆ, Željen TRPOVSKI, Vojin ŠENK

Faculty of Technical Sciences, University of Novi Sad
Novi Sad, Serbia and Montenegro
vecko@beotel.yu

Received: November 2002 / Accepted: July 2003

Abstract: A new, simple, fast and effective method for moving object detection in outdoor environments, invariant to extreme illumination changes is presented as an improvement to the shading model method described in [8]. It is based on an analytical parameter introduced in the shading model, background updating technique and window processing.

Keywords: Moving object, detection, illumination.

1. INTRODUCTION

In recent years extensive investigations and analyses have been done in the domain of moving object detection. Detection of moving objects in video processing plays a very important role in many vision applications. The vision systems that include image processing methods are widely implemented in many areas as traffic control [5]-[7], video surveillance of unattended outdoor environments [3], video surveillance of objects [1], etc.

The change detection algorithms implemented in these video systems provide low-level information that can be used by higher level algorithms to determine the information desired (the trajectory of an object, the control of traffic flow, etc). Methods for moving object detection must be accurate and robust so that complex video systems can operate successfully.

Most of the existing algorithms for moving object detection assume that the illumination in a scene remains constant. Unfortunately, this assumption is not valid, especially in outdoor environment. The efficiency of some of existing techniques diminishes significantly if the illumination varies.

There are two types of methods that realize moving object detection. One detects changes at pixel level and the other is based on feature comparison. The first method is better because of very fast detection of any kind of changes in the analyzed scene and it is implemented in the technique proposed in this paper.

Considering the fact that the image frequency in video sequence is 25 frames per second, the real-time video processing demands simple and fast algorithms. Simple differencing methods or fixed background extraction realized by various operations related to threshold determination are thus dominating in applications. The efficiency of these methods depends mostly on accuracy of background updating techniques and on the threshold choice.

In this paper we present a new, illumination independent method for moving object detection in outdoor environment, based on the shading model method [2]. It is shown in [6] that this method is superior to other techniques if the illumination is allowed to vary. The experiments shown in [2] have applied this method to the whole image. Since this is time consuming, only two successive frames were included. There was just a slight illumination change between them and new objects appeared in the second frame.

We apply the method [2] as a basis for moving object detection in video sequence with illumination changes. Two major improvements are proposed here:

- Processing of windowed segment of the image and
- Background updating technique.

We process only windowed segments of images where the moving object is expected. In this way we significantly reduce the execution time.

We also introduce background updating technique on a frame-by-frame basis. According to our experiments, the shading model method is effective only when applied in parallel with background updating. We introduced an improvement of this method that makes it work well even when there is a moving object detected in the scene (when background updating is locked out which makes the algorithm susceptible to illumination changes in that period).

A range of experiments with different type of illumination changes has proven the efficiency of the proposed method.

This paper consists of five sections. After the introduction, the shading model method and its improvement are introduced in Section 2. The third part describes the existing methods for background updating. Section 4 contains the experimental results of video analysis. Conclusions are given at the end.

2. THE SHADING MODEL METHOD

2.1. Moving Object Detection

Moving object detection algorithms usually take two consecutive images as input and return the locations where differences are identified. These differences can be caused by the motion of an object, (including its entering and leaving the scene), changes in illumination or noise. The aim of such an algorithm is to locate only the changes that are due to structural changes in the scene, i.e. a moving object.

Moving object detection and extraction from the fixed background in the analyzed scene is mostly done by simple subtracting the current image and background image (that does not contain any moving objects), [1, 3, 5, 6, 7].

The applied subtracting operation finds an absolute difference for each pixel, thus detecting moving objects (that have brighter or darker gray value), which usually differ from the background. If the difference is below a certain threshold, there is no change in the scene and the observed pixel is regarded as if it belongs to the background. Otherwise, there has been a change and the pixel belongs to the moving object. The absolute subtracting algorithm can be presented by

```
IF  $D = |C - B| > T$
    $O = 1$        (object)
ELSE                                                        ( 1 )
    $O = 0$        (background),
```

where *C* is the value of the corresponding pixel of the current image, B is the value of the corresponding pixel of the background image, *D* is the absolute difference of the current and background image and *O* is the binary difference image. *T* is the predefined threshold for image segmentation.

In the case of fixed threshold it can happen that a moving object with an average brightness, which is only slightly different than the background, cannot be detected. The value for threshold becomes very important because:

- If the threshold is too low, a sudden increase in background brightness due, for example, to a rapid change from overcast to sunshine, could cause a false detection.
- If the threshold is too high, a moving object with brightness close to the background will not be detected, [5].

The optimal threshold value is usually determined by analyzing the histogram of difference image in a certain time interval, where the appearance of moving object in the scene causes the histogram of difference image to widen. However, this is a time consuming process that is not effective in real-time applications.

The main problem with difference technique is a variation in background brightness, mostly due to weather phenomena (clouds, rain, etc.) or artificial sources (illumination, car or plane headlights, shadows, etc.).

In order to make the background differencing technique more effective, the changes in ambient lighting must be compensated by some kind of background updating technique.

2.2. The Shading Model Method

The shading model method determines whether structural changes occurred in the scene. It is shown that the shading model method is superior to other techniques when the illumination is allowed to vary [8].

The shading model method models the intensity of pixel I_p in the analyzed image according to:

$$I_p = I_i S_p , \tag{2}$$

where I_i is the illumination value and S_p is the shading coefficient. Phong's shading model [8] is one of many typical shading models used.

The main idea of the shading model is that it mathematically formulates the shading coefficient of every physical material, which is defined uniquely by the physical surface structure of the object and the reflectance of the surface material.

Unfortunately, it is not possible to calculate the shading coefficient for a given pixel without a priori knowledge of the surface structure. This task is very difficult, almost impossible to realize in real world applications. However, we do not need the exact value of the shading coefficient. We only need to detect a change in the shading coefficient to be able to indicate a change between the frames of the sequence. The shading model change detection algorithm uses the ratio of intensities recorded in a region of the two frames to detect this change. It is expressed by

$$\sigma^2 = \frac{1}{card\{A\}} \sum_{i \in A} \left(\frac{B}{C} - \mu_A \right)^2 \geq T , \tag{3}$$

where σ^2 is the variance of the intensity ratios, *B* is the background image that does not contain moving objects, *C* is the current frame of the scene, *A* is the observed region of interest of the processed image, $card\{A\}$ stands for the region size, *T* is predetermined threshold and μ_A is the average of the intensity ratio:

$$\mu_A = \frac{1}{card\{A\}} \sum_{i \in A} \frac{B}{C} . \tag{4}$$

Summation is performed pixel by pixel, over the region of interest.

If there are changes in the physical surface in the observed region (all the shading coefficients do not change in exactly the same manner), the average of the ratios' variance in that region is greater than zero.

To determine whether a change has taken place in a given region, one simply calculates the σ^2 in that region. If it is close to zero (less than certain threshold), there have not been any structural changes in the scene. Otherwise, we assume a structural change had occurred (the moving object has appeared in the image). The region of interest A should be large enough so that the statistics is indicative of the nature of the region. For the experiments, we used 3x3 regions because we observed only small image segments of dimensions 60x5.

This technique detects changes in physical surface structure and is, roughly, illumination independent. The shading model method is rather insensitive to noise [8].

2.3. Improved Shading Model Method

We made experiments (shown in Section 4) with various illumination changes considering the shading model method presented in [8]. We concluded that this method works well as long as the illumination changes are within +/–20% difference between background and current image. This method is not working for larger luminance changes. Therefore, we introduced the background updating technique in every frame that contains no moving objects in the scene. After the appearance of a moving object, background updating is locked out.

This algorithm becomes again susceptible to luminance changes while the moving object is in the scene. If, for example, a cloud appears or disappears, illumination difference would cause significant changes in the ratio between corresponding pixels of background image and current picture.

This is the reason why we have introduced a modification to the existing method. Instead of using the variance of $\frac{B}{C}$ from (3), we introduced a new coefficient that measures the ratio between average pixel value of the first frame when the moving object entered the scene and average pixel value of every current frame while the moving object is in the scene, i.e. while the background updating process is locked out. We also used median value of all pixels that belong to the region A, instead of mean value in the variance value calculation because this accelerates the whole algorithm. The comparison operation is faster then addition and division used for mean value calculation.

The mathematical expression of improved version of shading model method is given by

$$\sigma_I^2 = \frac{1}{card\{A\}} \sum_{i \in A} \left(\frac{B}{C} * coef - median_A \right)^2 \geq T \,, \tag{5}$$

where σ_I^2 is the improved variance of the ratio of the background and the current frame (compared to σ^2 in (3)), and the $coef$ is determined by

$$\begin{aligned} & coef = 1 \ \text{(the beginning coefficient value)} \\ & \text{IF} \ \ \sigma_I^2 = \frac{1}{card\{A\}} \sum_{i \in A} \left(\frac{B}{C} * coef - median_A \right)^2 \geq T \\ & \text{THEN} \ \ coef = \frac{\frac{1}{card\{A\}} \sum_{i\in A} C_{ni}}{\frac{1}{card\{A\}} \sum_{i\in A} C_{1i}} = \frac{\mu_n}{\mu_1} \\ & \text{ELSE} \ \ coef = 1 . \end{aligned} \tag{6}$$

where μ_n is the average of the current frame while the moving object is present in the scene, μ_1 is the average value of the first frame after the moving object entered the scene, and T is a threshold which determines whether there was a structural change in the observed scene or not.

If σ_I^2 is greater than T, it is assumed that the moving object entered the observation window.

At that moment, we memorize the average value of the first window μ_1 just one frame before the moving object entered the scene so that it would not contain a contribution from the moving object[1]. In all the following frames, while the moving

[1] The modification was made in accordance with the suggestion of the unknown referee.

object is present in the scene, we compute the average value of every current window μ_n and *coef* represents the ratio of these two mean values, i.e. it compensates possible illumination changes while background updating is locked out.

When σ_I^2 becomes less than predetermined threshold *T*, it means there are no more moving objects present in the observed scene, so the *coef* is set to 1. Background updating method functions again and there is no need for compensation using *coef.* The initial value of *coef* is set to one.

3. BACKGROUND UPDATING

Every change of illumination in the analyzed image demands an adequate background updating. However, the interruption of image processing in real-time for background updating is not always possible. Thus, the background updating method must be simultaneous with image processing.

The simplest algorithm for background updating is the moving averaging updating technique, described in [2] as

$$B_{n+1} = kB_n + (1-k)C_n\,, \tag{7}$$

where B_{n+1} is the updated background image, used for moving object extraction from the next image in the sequence, B_n is the previous background image and C_n is the current image, k is the constant that determines the updating rate. Typical values of k are ≈ 0.5 so that the influence of the current picture on background updating is equal to the influence of the previous background frame. The most important drawbacks of this method are the following: the moving object appears in the background image and the optimal choice of k is almost unsolvable problem.

Illumination changes in the scene are usually smaller then those due to the moving object in the analyzed image. This fact implies the possibility that the background updating is applied only to those segments of the analyzed scene that are not covered with the moving object. Pseudocode of this technique, applied on pixel level, is described by

```
IF ($D_n = | C_n - B_n | > T$)
    $O_n = 0$ (object)
    $B_{n+1} = B_n$ (no background updating, there is a moving object in the scene)        (8)
ELSE
    $O_n = 1$ (background)
    $B_{n+1} = kB_n + (1-k)C_n$ (background updating, no moving objects in the scene).
```

This algorithm shows better results than the previous background updating algorithm. But the effectiveness and the quality of the selective background updating technique mostly depends on the proper choice of the threshold value *T*, which implies a compromise between background updating and moving object detection quality. If the threshold is not selected properly, the moving object pixels are misclassified as the background pixels. The background image becomes unusable.

Previously described techniques for background updating could be combined, giving selective background updating with averaging that provides new quality [2]. Here, the background of the selected pixels is replaced by the average of the current and background picture pixels $(k = 0.5)$, instead of directly replacing the background pixels by the current image pixels.

We have implemented selective background technique with averaging only in those frames where the average value of variance of the ratio of background and current picture gave binary picture which number of pixels that indicate the moving object exceeded certain threshold.

In this paper, we combine the before mentioned methods into the following algorithm:

```
$coef = 1$ (the beginning coefficient value)
IF ( $\sigma_I^2 = \frac{1}{card\{A\}} \sum_{i \in A} \left( \frac{B}{C} * coef - median_A \right)^2 \geq T$ )
    $O_n = 0$ (object)
    $B_{n+1} = B_n$ (no background updating, there is a moving object in the scene)
    $coef = \frac{\frac{1}{card\{A\}} \sum_{i \in A} C_{ni}}{\frac{1}{card\{A\}} \sum_{i \in A} C_{1i}} = \frac{\mu_n}{\mu_1}$
ELSE                                                                          (9)
    $O_n = 1$ (background)
    $B_{n+1} = (B_n + C_n)/2$ (background updating, no moving objects in the scene)
    $coef = 1$.
```

4. RESULTS

The new algorithm is applied to the analysis of video sequence that shows a passenger plane rolling on the runway. The sequence contains 49 monochrome images, 640x480 pixels with 256 gray levels (8 bits). Video rate is 25 frames per second.

The images are too large for real-time implementation of the image-processing algorithm.

Since it is not necessary to analyze and update the whole image, but just the segment, which is of interest, on the expected path of the moving object, we have included this improvement into our algorithm.

The section of interest is presented by rectangular window 5 pixels wide and 60 pixels high, perpendicular to the expected path of the moving object. We have analyzed five windows of this shape placed at distance of ten pixels along horizontal direction. They are placed at the horizontal range 21-25, 31-35, 41-45, 51-55 and 61-65, respectively and the vertical range is 171-230. The results obtained from each of these windows were used to get the final score. The height of these windows is some 10% larger than the expected height of the moving object. Windows are located so that the moving object passes through their center.

The proposed algorithm was tested under various lighting conditions gained artificially on real video sequences. The algorithm allows the user to define regions.

Figure 1 represents the background without moving objects and Figure 2 represents the airplane in the 45th frame.

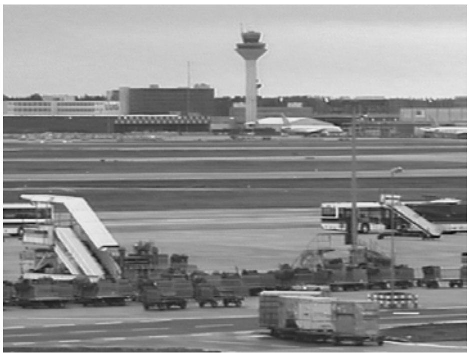


Figure 1: Background image

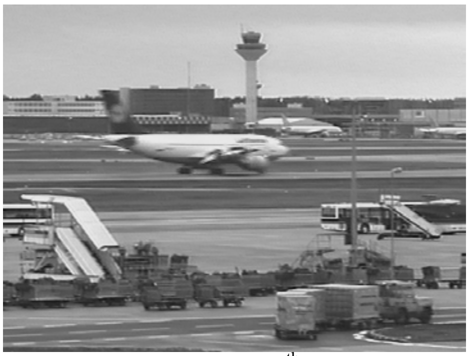


Figure 2: 45th frame

Figures 3 and 4 show the result of processing the whole image with shading model method masks (size 3x3). We have made experiments with different mask size (for example 5x5), but the results obtained with larger masks did not compensate the significantly greater execution times.

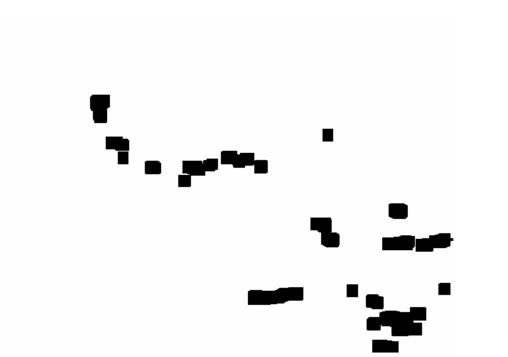


Figure 3: The binary image obtained with the application of the shading model method, [7]

Figure 4: The binary image obtained with the application of the improved shading model method

We have applied the plain shading model method [8], the improved shading model method and selective background updating technique with averaging. All images were post processed. The binary image obtained with the plain shading model method was first median filtered with the 7x7 mask and then treated with the dilation technique with 15x15 mask. This was inevitable to get the best possible results but this post processing is also very time consuming.

On the binary image obtained with the new algorithm the dilation technique with 15x15 mask was applied only.

Figure 3 represents the binary image obtained by the application of the plain shading model method (3) with 3x3 mask and the threshold level of 0.25. Figure 4 is the binary image that emphasizes the moving object obtained by the application of the new method (9) with 3 x 3 mask and threshold level of 0.1.

Comparing Figures 3 and 4 with the video sequence, it is obvious that the proposed technique gives significantly better results. According to Figure 4, two moving objects are present in the scene, airplane (on the left) and the truck (in the lower right corner of the image), as seen in the video sequence.

The results reported here are obtained for the first window, located at the coordinates 21-25 horizontally and 171-230 vertically. The airplane enters the window in the 4th frame and leaves it in the 36th frame.

Several other experiments were done on this video sequence. It can be noticed that the moving object is brighter than the background. We didn't have video sequences with sudden luminance change and with the moving object darker than the background. However, we have simulated these conditions, the first one with illumination variations and the second one by inverting the original sequence.

Experiments were divided into two groups. The first group is performed on the original sequence of images (the moving object is brighter than background) and the second one on the inverted video sequence (the moving object darker than background).

Nine experiments were done, with eight different methods. Results are given in Table 1, a column per each experiment.

1) Original video, column 1.
2) The luminance change began, continued and stopped while the moving object was permanently present in the observed scene. This experiment could simulate the real situation when cloudy and its shadow appears while there is a moving object in the scene. The illumination change lasted 20 consecutive frames, from 11th to 30th frame (0.8s). We have done five experiments of this kind considering different levels of luminance changes. We decreased illumination level to 90%, 80%, 70%, 60% and 50% of the initial luminance level, respectively. Only the results with 50% luminance level change are shown here because they exhibit the extreme situations, column 2.
3) The illumination level is increased while the moving object was permanently in the scene from 50% to 100% of the initial luminance level, from 11th to 30th frame, column 3. The luminance increase was performed on the sequence where the illumination decrease was already done so the maximum illumination level was not violated.
4) The luminance decrease lasted 20 frames (0.8s), starting while the moving object was in the scene (20th frame), until the 40th frame. This simulates the real situation when cloudy and its shadow appear while there is a moving object in

the scene and the shadow is still present after the moving object leaves the scene. Several luminance changes were performed as in previous experiments but only the results with the decrease of 50% are shown, column 4.

5) The luminance increase of 50% under the same conditions, from 20th to 40th frame, column 5.
6) Sudden luminance change (50% decrease) during the 20th frame (in 0.04s), column 6.
7) Sudden luminance increase of 50% in 20th frame, column 7.
8) Sudden luminance decrease of 50%, when the moving object is not present in the observed scene, in the 40th frame, column 8.
9) Sudden luminance increase of 50%, also in the 40th frame, column 9.

The proposed new algorithm has given good results in all experiments. The moving object was always detected and there were no false alarms.

For comparison, we have performed the same experiments, with application of existing known methods.

The following eight methods are given in rows of Table 1.

I. The new method,
II. The SMED operator [2],
III. Inigo technique [5],
IV. Improved version of differencing with selective background updating technique with averaging [2],
V. Change detection method [4],
VI. The Skifstad and Jain method [8],
VII. The Skifstad and Jain method applied only with introduced coefficient without background updating,
VIII. The Skifstad and Jain method in parallel with the technique of background updating but without the coefficient.

Table 1.

Algor/Exp.	1.	2.	3.	4.	5.	6.	7.	8.	9.
I	100 0	100 0	100 0	100 0	100 0	100 0	100 0	100 0	100 0
II	96,97 0	96,97 81,25	75,76 75	96,97 81,25	51,52 0	84,85 0	66,67 81,25	96,97 0	54,55 25
III	87,88 0	100 81,25	100 81,25	100 81,25	100 81,25	100 81,25	100 81,25	87,88 62,50	87,88 62,5
IV	96,97 0	100 75	69,70 75	100 75	27,27 75	100 75	39,39 75	96,97 56,25	0 56,25
V	96,97 0	100 81,25	100 81,25	100 81,25	100 81,25	100 81,25	100 81,25	96,97 62,50	93,94 62,5
VI	81,81 12,5	90,90 56,25	60,60 0	90,90 56,25	72,72 0	90,90 56,25	66,67 0	81,81 50	81,81 0
VII	81,81 12,5	87,80 56,25	69,69 0	87,87 56,25	72,72 0	87,87 56,25	66,67 0	81,81 50	81,81 0
VIII	93,93 0	93,93 81,25	84,85 81,25	93,93 81,25	90,90 12,50	93,94 81,25	90,90 81,25	93,94 0	93,94 0

For each method and experiment, two numbers are given. The first one describes the percentage of correct detection in the observed window. The division of the sum of the number of frames realized this calculation where the moving object was correctly detected, with the sum of all the frames in the observed sequence where the moving object really appears, multiplied with 100%. The second one indicates the percentage of false alarms in the observed window. This percentage was realized by the division of the sum of the number of frames where the moving object was incorrectly detected by the algorithm, with the sum of all the frames where the moving object does not appear, multiplied with 100%. As mentioned earlier, the moving object is present in 33 of total 49 frames, from 4th to 36th frame.

The superiority of proposed method over the existing techniques is obvious.

We have presented some of the results in graphical form.

The *x* axis (time axis) in Figures 5 and 6 represents the ordinal number of the processed frame, in the range 1-49. The *y* axis shows the number of black pixels that represent the detected moving object in the observed window.

The following Figures illustrate more detailed representation of the mentioned methods under various illumination conditions. They show the absolute difference, of detected pixels that represent the moving object, between the normal sequence and the sequence with luminance change observed through frames, in other words, in time.

Figure 5 shows the absolute difference between the results in column 1 and column 2 for the following methods: I (marked with the solid line), II (plus line), IV (circle line), V (dashed line) and VI (the star line). The absolute difference means the difference between the number of correctly detected pixels that really belong to the moving object in the first and the second experiment.

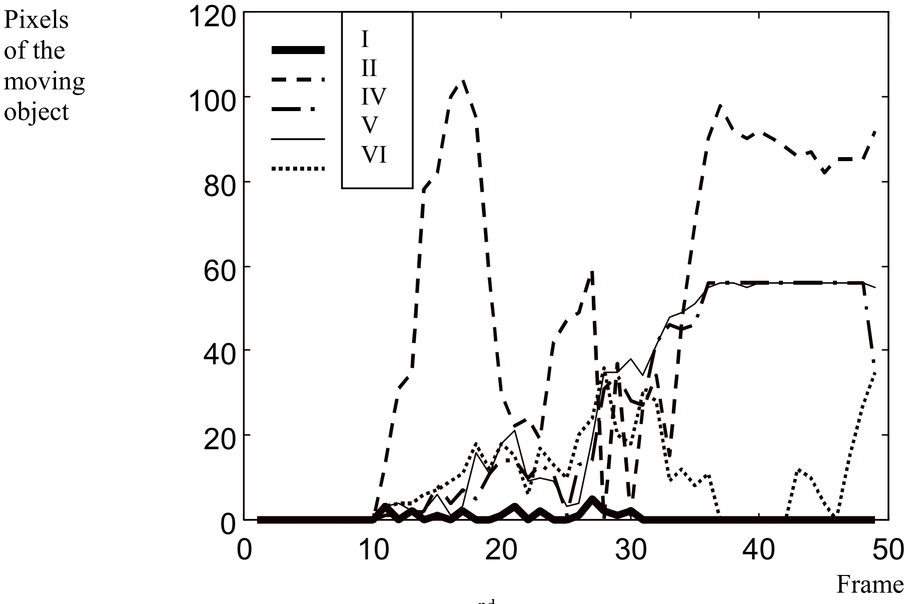


Figure 5: Results for the 2nd experiment, methods I, II, IV, V and VI

Figure 6 shows the absolute difference between the results from column 1 and column 7 for mentioned methods.

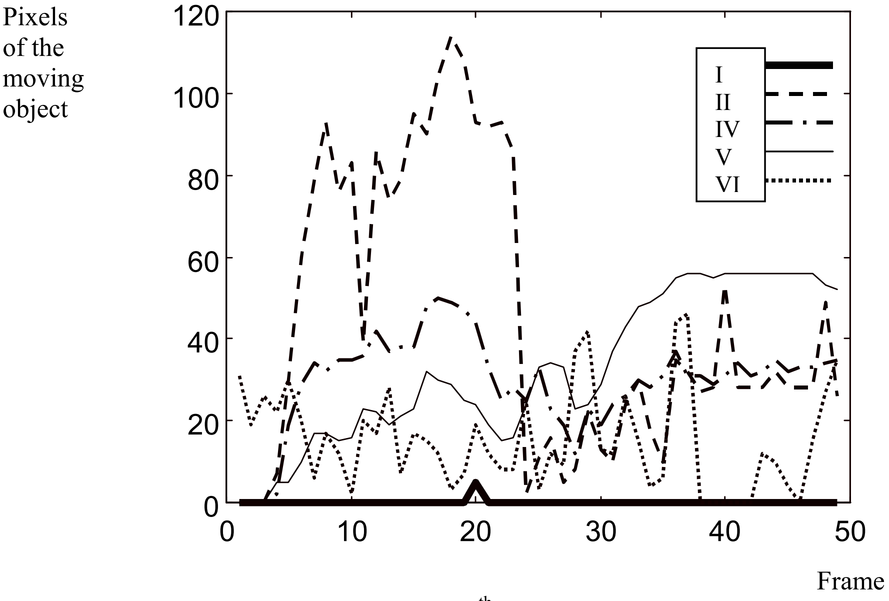
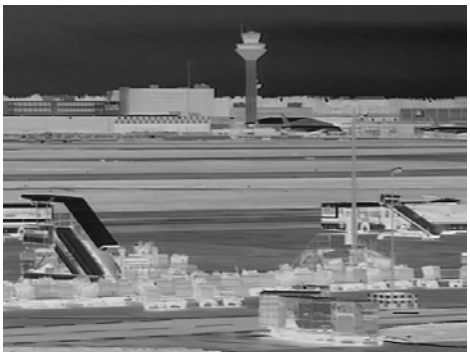


Figure 6: Results for the 7th experiment, methods I, II, IV, V and VI

The superiority of the proposed method is quite obvious. It almost does not change its behavior with illumination changes, while other methods seriously deteriorate.

For the second group of experiments the inverted video sequence has been used.

Figure 7 shows the artificially processed, inverted background image and Figure 8 represents 45th frame that contains moving object, which is darker than the background.



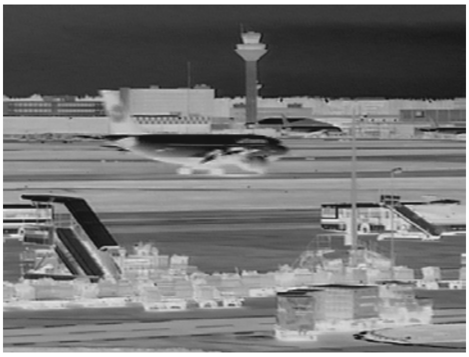


Figure 7: Inverted background image

Figure 8: Inverted 45th frame

We have applied the new algorithm to these two images with 3x3 masks.

Figure 9 represents the binary image obtained by the application of the plain shading model method with the threshold level 0.25 and Figure 10 is the binary image that emphasizes the moving object obtained by the application of the new method (11) with the threshold level 0.1.

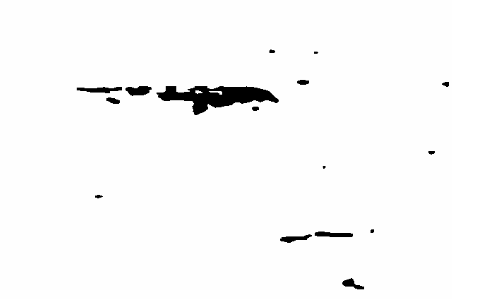


Figure 9: The binary image obtained with the application of the shading model method, [7]

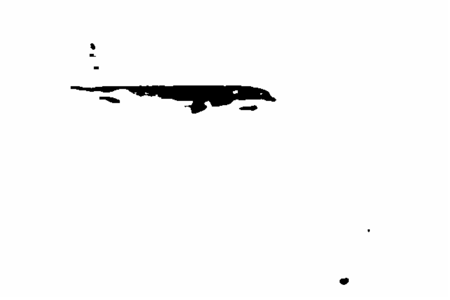


Figure 10: The binary image obtained with the application of the improved shading model method

We have also applied median filtering with 7x7 mask and dilation with 15x15 mask.

It is obvious that the new technique gives significantly better results with fewer false alarms. Comparing Figures 4 and 10 it is obvious that (with the inverted video sequence) we obtain binary image, which better defines the moving object. For these reasons we didn't have to apply the process of dilation.

The same nine experiments were repeated for the inverted images. The results for all experiments are very promising. The percentage of correctly detected moving object was 100% and there were no false alarms.

All these results show that the proposed algorithm is not sensitive neither to slow nor fast illumination changes.

Table 2.

Algorithm	1.	2.	3.	4.	5.	6.	7.	8.	9.
I	100 0	100 0	100 0	100 0	100 0	100 0	100 0	100 0	100 0
II	96,97 0	75,76 0	54,55 81,25	84,85 0	54,55 81,25	75,76 0	78,79 81,25	96,97 0	54,55 81,25
III	96,97 0	100 75	24,24 75	100 75	100 81,25	100 81,25	100 81,25	87,88 62,50	84,85 62,50
IV	96,97 0	100 81,25	100 81,25	100 81,25	24,24 75	100 75	51,52 75	96,97 56,25	0 56,25
V	96,97 0	100 81,25	100 81,25	100 81,25	100 81,25	100 81,25	100 81,25	96,97 62,50	90,90 68,75
VI	100 18,75	100 62,50	100 6,25	100 62,50	100 6,25	100 62,50	100 6,25	100 56,25	100 6,25
VII	100 18,75	100 62,50	100 6,25	100 62,50	100 6,25	100 62,50	100 6,25	100 56,25	100 6,25
VIII	100 0	100 81,25	100 0	100 75,00	100 0	100 81,25	100 0	100 0	100 0

For the comparison reasons we have done the same experiments on the inverted sequence with application of existing known methods mentioned above. All these methods showed to be subtle to illumination changes, which is obvious from the Table 2.

The structure of the Table 2 is the same as for the Table 1 as well as the way the results are presented.

We have presented some of the results in graphical form.

In Figures 11 and 12 the x-axis represents the number of processed frame i.e. the time and y-axis shows the number of black pixels that represent the detected moving object in the observed window.

Figure 11 represents the graphic of absolute difference between the results from column 1 and column 5 for mentioned methods.

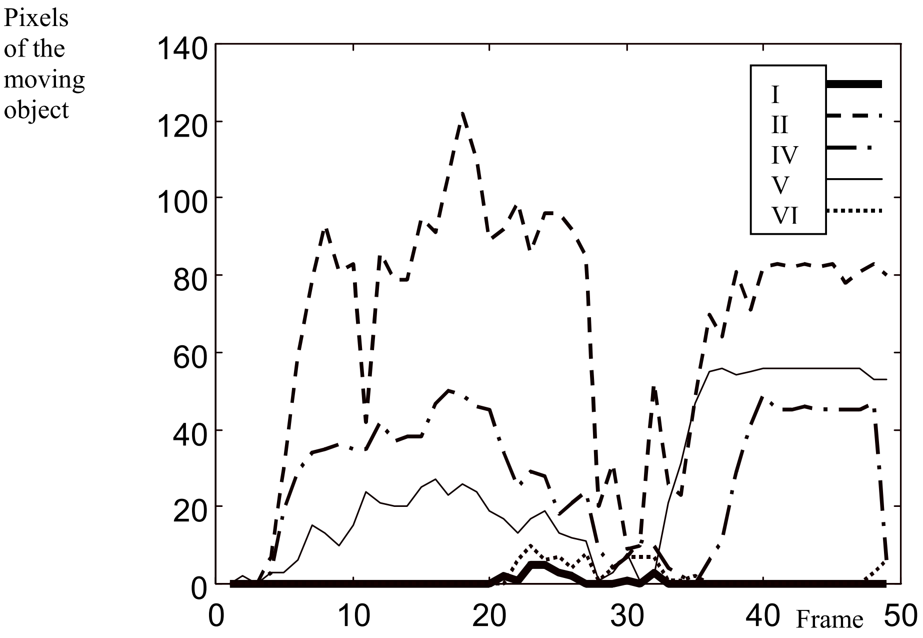


Figure 11: Results for the 5th experiment, methods I, II, IV, V and VI

Figure 12 represents the absolute difference between the results from column 1 and column 9 for mentioned methods.

The previous Figures illustrate the superiority of the proposed method even in the case when the moving object is darker than the background. This technique remains resistant to illumination changes while other methods obviously fail. It also succeeds to handle the completely correct detection of the moving object under luminance variation while other techniques completely lose control.

We must emphasize that the only reliable way to entirely check the effectiveness of this method would be the real-time testing. However, the presented simulations and experiments give very promising results.

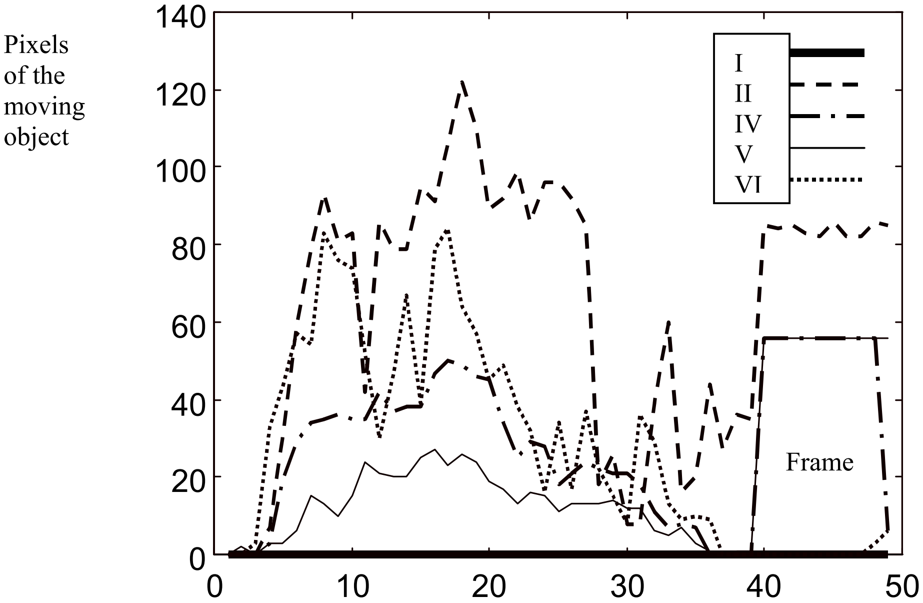


Figure 12: Results for the 9th experiment, methods I, II, IV, V and VI

5. CONCLUSION

The problems associated with the background-based moving object detection techniques are mainly due to the variations of ambient lighting. In this paper we introduced an effective moving object detection algorithm based on the shading model method with background updating technique under conditions where illumination cannot be controlled.

The new method is shown to be invariant to significant illumination changes and superior to other techniques when the illumination is allowed to vary.

In order to accelerate the execution time of the whole algorithm, we have processed only certain segments of images where we expected to find the moving object. We also used median value of the observed region A, instead of mean value in calculating the variance because the comparison is faster then addition and division (necessary for calculating the mean value).

We have also introduced the process of background updating in this technique, along with the shading model method, applied at every frame. The shading model method has shown to be effective only when applied in parallel with background updating. That is why we introduced an improvement of this method that makes it function well even when there is a moving object detected in the scene (when background updating is locked out which makes the algorithm susceptible to illumination changes in that period).

The new described algorithm was applied on three more video sequences and it also showed very good and promising results. One was also grey as the one used presented in this paper, and two others were colored. One of the colored sequences had two moving objects. The proposed method succeeded to completely successfully detect the both moving objects in the scene independently of the luminance conditions. We showed in this paper the results obtained from the one of the used sequences that was the most convenient for the representation.

The proposed algorithm, invariant to external luminance changes, has been tested under various lighting conditions, artificially simulated on the computer and with the moving object brighter and darker than the background, and satisfactory and promising results have been achieved.

Acknowledgement. The authors wish to acknowledge the unknown referee, for the useful suggestions that improved the presented new method.

REFERENCES

[1] Corrall, D., “VIEW: Computer vision for surveillance applications”, *IEE Colloquium Active and Passive Techniques for 3D Vision*, IEE, London, 8 (1991) 1-3.

[2] Fathy, M., and Siyal, M.Y., “An image detection technique based on morphological edge detection and background differencing for real-time traffic analysis”, *Pattern Recognition Letters*, 16 (1995) 1321-1330.

[3] Foresti, G.L., “A real-time system for video surveillance of unattended outdoor environments”, *IEEE Transactions on Circuits Systems and. Video Technology*, 8 (6) (1998) 697-704.

[4] Foresti, G.L., and Regazzoni, C.S., “A change detection method for multiple object localization in real scenes”, *IEEE*, 1994, 984-987.

[5] Inigo, R.M., “Application of machine vision to traffic monitoring and control”, *IEEE Transactions on Vehicular Technology*, 38 (3) (1989) 112-122.

[6] Mecocci, A., “Moving object recognition and classification in external environments”, *Signal Processing*, 18 (1989) 183-194.

[7] Rourke, A., Bell, M.G.H., and Hoose, N., “Road traffic monitoring using image processing”, *3rd International Conference on Road Traffic Control*, London, May 1-3, 1990, 163-167.

[8] Skifstad, K., and Ramesh, J., “Illumination independent change detection for real world image sequences”, *Computer Vision, Graphics, and Image Processing*, Vol. 46, 1989, pp. 387-399.