MOVING OBJECT DETECTION UNDER SIGNIFICANT CHANGES OF LIGHTING

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ABSTRACT

Surveillance applications require reliable components with capabilities to work under disturbance conditions such as momentary power interruption. The research leading to this paper has been focused on implementing a robust algorithm to detect movement of foreground objects independent of illumination changes. An improved version combining time and space analysis is presented. Experimental results show a promising advance in the addressed problem.

1. INTRODUCTION

Real-time moving objects detection is an interest research topic with a recognized impact in practical applications such as traffic regulation [1]-[4] and video surveillance [5]-[7]. Proposed methods must be fast, simple and computationally feasible in order to comply the requirements of real-time systems.

Commonly, those methods use algorithms based on segmentation of the fixed background varying a decision threshold. Consequently, their accuracy depends significantly on the suitable threshold selection as well as on the precision of the background updating technique.

Nakai proposes a statistical model to reduce the noise produced by movements of background objects [8]. A shortcoming is in the decreasing sensitivity of the target detection. Iketani et al uses a predicted path voting method that can work under various disturbances by accumulating information over space and time [9].

In contrast, a simplest method, which exploits temporal and spatial information, is presented. It is an improved version of our previous approaches [10][11].

The next Section introduces the mathematical formulation on which the method is based. Section 3 describes the proposed approach. Experimental results are analyzed in Section 4. Concluding remarks appears in Section 5.

2. MATHEMATICAL FORMULATION

Let I be an image sequence consisting of N video frames and A_i a sliding mask applied on every frame.

In [12] Skifstad and Jain use the ratio of pixel intensities in mask A_i between two a reference and a current frame to estimate the pixel variance σ_i^2 as follows:

$$\sigma_i^2 = \frac{1}{card\{A_i\}} \sum_{m \in A_i} \left(\frac{B_m}{C_m} - \mu_{A_i} \right)^2, \; i = 1..n. \tag{1}$$

where μ_{A_i} denotes the mean of the pixel intensity ratio within A_i, B_m (reference background frame) contains pixel intensities within A_i and C_m is the current frame where moving objects are being identified.

The center of the sliding window A_i is marked as changing region if the following condition is satisfied:

$$\sigma_i^2 \geq \varepsilon \tag{2}$$

where $\varepsilon > 0$ is a suitable threshold.

Experiments presented in [1-7] show that for significant illumination changes this method fails, i.e. some pixels are falsely assigned to changing regions. Some modifications based on adaptive coefficient for illumination compensation were introduced in [10] and [11]. In there, pixel variance is estimated as:

$$\sigma_i^2 = \frac{1}{card\{A_i\}} \sum_{m \in A_i} \left(\frac{B_m}{C_m} K_i - median\{A_i\} \right)^2, \tag{3}$$

The median is used instead of mean value in order to reduce sensitivity introduced by outliers. Then, the illumination compensation coefficient is defined as

$$K_i = \frac{\sum_{m \in A_i} C_m}{\sum_{m \in A_i} C_{1m}} = \frac{\mu_i}{\mu_1}, \tag{4}$$

where C_{1m} is pixel intensity for the first frame in the sequence.

3. PROPOSED METHOD

In Equation 4, the coefficient K_i enables sensitivity suppression in the shading model method. It is fairly robust to significant and sudden illumination changes (up to roughly 50% of change in comparison to the starting illumination level).

Introduced temporal and spatial analysis allows detection of the inner parts of the moving objects as well as the thicker edges. This is used to reduce false detection.

Analysis is performed by computing the average of pixel variances (Equation 3) for three successive pairs of frames:

$$\sigma_{mean}^2 = (\sigma_i^2 + \sigma_{i+1}^2 + \sigma_{i+2}^2) / 3, \tag{5}$$

where i indicates the frame index.

In contrast to Equation 2, the center of the sliding window A_i is marked as changing region if the condition

$$\left|\sigma_i^2 - \sigma_{mean}^2\right| \geq \varepsilon \tag{6}$$

is satisfied.

4. EXPERIMENTAL RESULTS

The proposed method was tested using a number of real-world videos. In order to illustrate the experimental results, a sample video sequence is presented below. The sequence corresponds to a person walking across a room whilst artificial illumination is turned off and on to simulate momentary power interruption. As illustrated in Figure 1, the illumination decreases about 50% and later on it is reestablished to the previous level.

Analysis is performed on 94 frames with resolution of 352×288 pixels. The image frequency is 25 frames per second. The reference background, B_m in Equation 1, is depicted in Figure 1.a and contains part of the floor and office furniture (chair and desk).

Figure 1.b and 1.c show the 30th and 86th frames, respectively, containing the moving object—the person walking across the observed scene.

The sliding window A_i was set up to 3×3 pixels and an optimal threshold was experimentally found to be $\varepsilon = 0.01$.

The binary images of the frames used as reference are presented in Figure 2. In these and the subsequent figures, changing regions are marked with white pixels.

Although the previous version achieves an acceptable accuracy for detecting the moving object, it reported more false alarms during the experiments. The new version behaves better in detecting inner parts of the moving object. In addition, it is able to detect thicker objects.

The capabilities of the new version are exemplify in Figure 2 using a rectangular window. The changing regions are detected inside the window. Those regions correspond to the moving object.

Figures 3.a and 3.b show the portion of window occupied by the moving object. The vertical axis represents the number of white pixels that represent the moving object, and horizontal axis shows the serial number of the processed frame in the sequence.

5. CONCLUSIONS AND FURTHER WORK

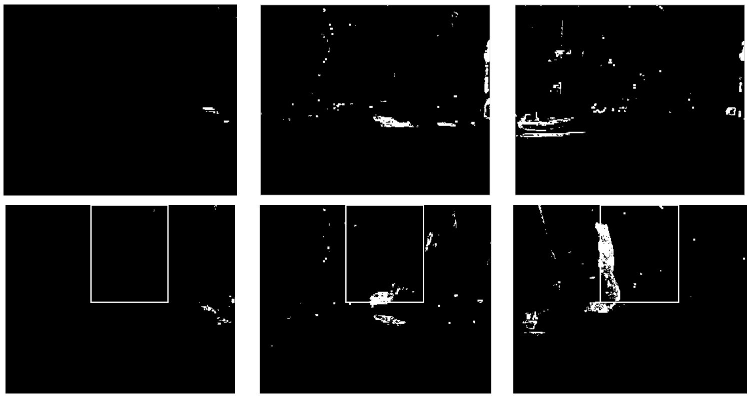
An improved version of a method for moving object detection, which is independent of illumination changes is presented. The new version uses temporal and spatial analysis to increase accuracy by reducing false alarms. Additionally, the method allows detection of inner parts in the moving objects.

Experimental results show that the proposed method is highly resistant to significant illumination changes. In most cases it succeeds to detect changing regions under significant luminance variations.

Further work will be addressed towards noise reduction and proposing a solution for the ghost problem. The increase of the threshold will reduce the noise and also the thickness of the moving objects. So the next task for the future work would be to deduce optimal threshold value.

(a) First frame (b) 30th frame (c) 86th frame

Figure 1. Frames in the video sequence used for the empirical analysis.



(a) First frame (b) 30th frame (c) 86th frame

Figure 2. Previous and new versions of the method are presented in the first and second rows, respectively. The box illustrates the changing region detection inside a given window.

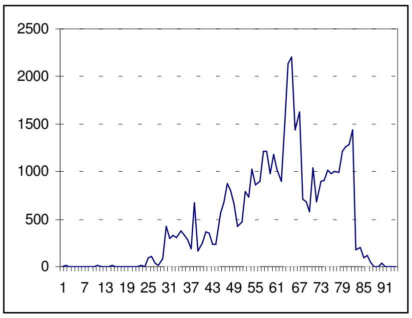


Figure 3. Number of changing pixels inside the window detected with the previous version.

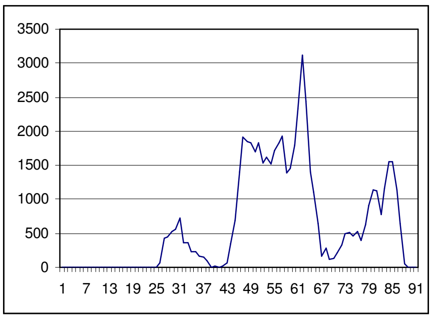


Figure 4. Number of changing pixels inside the window detected with the new version.

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