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Dynamic Background Updating for Lightweight Moving Object Detection

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***Abstract*—**Background subtraction and temporal difference are often used for moving object detection in video. Both approaches are computationally simple and easy to be deployed in real-time image processing. However, while the background subtraction is highly sensitive to dynamic background and illumination changes, the temporal difference approach is poor at extracting relevant pixels of the moving object and at detecting the stopped or slowly moving objects in the scene. In this paper, we propose a simple moving object detection scheme based on adaptive background subtraction and temporal difference exploiting dynamic background updates. The proposed technique consists of histogram equalization, a linear combination of background and temporal difference, followed by the novel frame-based and pixel-based background updating techniques. Finally, morphological operations are applied to the output images. Experimental results show that the proposed algorithm can solve the drawbacks of both background subtraction and temporal difference methods and can provide better performance than that of each method.

***Keywords*—**Background subtraction, background updating, real time and lightweight algorithm, temporal difference.

I. Introduction

THE moving object detection is one of the widely opened research fields in computer vision. It has vast applications in many areas, such as Unmanned Air Vehicles (UAV), video surveillance, detection of pedestrians and vehicles and so on. There has been a great deal of development in this field during the past decades. There are several approaches for achieving moving object detection; however, the most commonly used techniques can be categorized into background subtraction, temporal difference and optical flow [1].

The background subtraction is commonly used for motion segmentation in the static scene [2]–[6]. In the background subtraction, the background model should be created first. The background image can be modeled by averaging images over time during the initialization period. Moving regions are detected by measuring pixel-to-pixel deviation of the input image from the background image. If the deviation is above a threshold value, it will be detected as a moving region. Although the background subtraction technique performs well at extracting the relevant pixels of moving regions, it is highly sensitive to drastic background changes, for instance, when the stationary objects are uncovered the background or sudden illumination changes occur.

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In the temporal difference approach, moving objects are detected by taking pixel-to-pixel difference of consecutive frames (two or three) in the video sequence [7]-[10]. This method is highly adaptive to dynamic background as the most recent frames are involved in the computation of the moving region detection. However, it fails to extract all relevant pixels of the moving object as well as to detect slowly moving or stopped objects in the scene, because the last frame is taken as a reference for the current frame in the video sequence.

The optical flow methods make use of the optical flow vectors of moving object over time to detect a moving region in the image [11], [12]. In this method, the velocity and direction of each pixel should be computed. It is effective for detecting a dynamic motion in both moving camera and dynamic background environment. However, it is time consuming and has severe computational overheads to be used in real-time.

This paper presents an approach of utilizing both the background subtraction and temporal difference in combination so that it can be used in real-time image processing systems. The shortcomings of background subtraction can be overcome by the complementary temporal difference technique and vice versa. We note that the drawbacks of both approaches are in the following aspects. They are illumination changes, dynamic background changes and fail to detect a stopped or slowly moving object in the scene. The proposed approach addresses the above stated challenges of both methods.

This paper is organized as follows. In Section II presents the proposed algorithm. The experimental results are presented in Section III. Finally, some concluding remarks are presented.

II. The Proposed Algorithm

This section presents the details of the proposed approach. The block diagram of Fig. 1 shows the scheme of adaptive background subtraction and temporal difference for light weight moving object detection.

A. Illumination Equalization and Noise Reduction

This section presents a pre-processing to compensate for illumination effects. In this step, the RGB color space of the input image is converted into YCbCr color space. Then the YCbCr splits into three channels. Then the histogram equalization is applied to the Y (luminance) channel. Then the Y channel is merged with the remaining channels. Then it is converted again to the original RGB color space.

By applying the histogram equalization, the intensities of the image can be better distributed on the histogram. This let area of lower contrast gain a higher contrast. The histogram equalization helps to minimize the problems due to the illumination changes as well as to improve detecting the foreground. The median filter is then employed to reduce the noise in the image and to increase the quality of post-processing.

B. Moving Object Detection by Exploiting Dynamic Background Updates

A main target of this paper is to detect moving objects, especially the stopped and slowly moving objects (where the speed of the object is less than the frame rate, usually 30 frames per second), when the background in the scene is dynamic. It is known that this can be achieved neither with only traditional background subtraction nor with temporal difference technique. For example, if we take parking lot surveillance, the background subtraction method can detect some moving objects as long as the background is static. In the same case, if the temporal difference is used, it can detect the moving region with less false positive detections even in the case of dynamic background changes. However, it is not possible to extract all relevant pixels of the dynamic object and totally fail to detect when the speed of the foreground object is too slow or the foreground is stopped at the scene.

The proposed approach is capable of detecting the foreground in any state whether it is moving or stopped. In addition, it can detect a dynamic object, even in the drastic background change. Here the following parameters are defined. The number of detected pixels as part of moving area is represented by DP_{num} (the detected pixel numbers per frame) and CDP_{num} is a critical number of detected pixels per frame, which is the minimum number of detected pixels to trigger the background image to be updated by a new frame. The duration of stopping state where the object is counted as stopped object at the scene, is represented by Γ and the maximum duration to be detected as stopped object is represented by ‘SS’.

Fig. 1 shows a flowchart of the proposed algorithm. Let f_t, f_{t-1} and f_{bg} be the current input frame, the previous frame and the background image respectively. First the image convolved with the median filter is converted into a grayscale level. Then the intensity value of the current frame is compared with the previous frame pixel-by-pixel. If the estimated deviation is beyond the predefined threshold (*th*) or equal, then the corresponding pixel precedes to the next process. Next the pixel passed by the above process is again compared with the corresponding background pixel. If the absolute difference is above the threshold value, then the pixel is counted as it belongs to the moving region of the image.

In parallel two simple techniques are used to update the background image iteratively. The first one is a frame-based background updating method. The operation of frame-based approach is presented in the following statements. When the total number of detected pixels per frame (DP_{num}) is above the critical number of detected pixels per frame (for example, CDP_{num} is 60% of total pixels per frame), the background image is updated by that particular frame. The updated background image starts to be used in the next iteration.

There are also situations that do not require updating of the full frame but needs only some part of the background image to be updated. To achieve this, the second method called by the pixel-based background updating method is employed. Here we should note that the motionless objects should be identified as stopped only for the duration of less than the pre-defined maximum stopped state duration (SS). The algorithm keeps checking the status of each pixel in the frame, if they are classified as pixels of the foreground image. If the particular pixel is continuously detected as a pixel of moving region for the duration greater than SS, then the intensity value is assigned to its corresponding pixel in the background image.

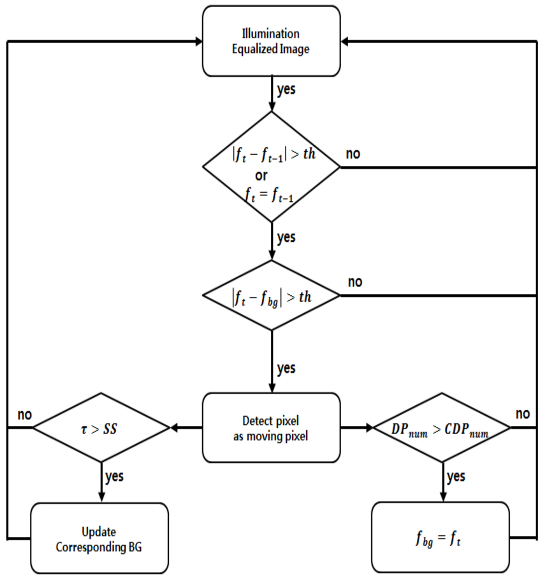

Fig. 1 Moving object detection with dynamic background change

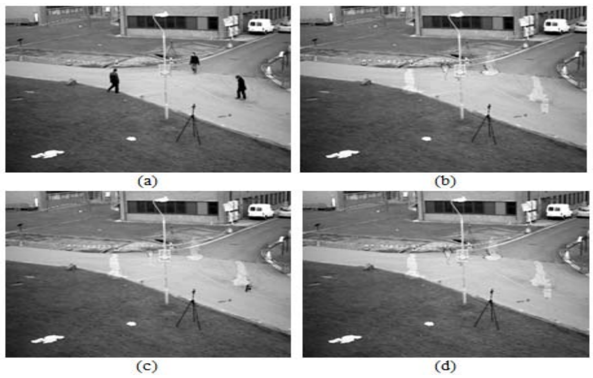

Fig. 2 Typical results of gradually updated background image by the proposed algorithm: (a) first frame of the video, (b) background frame at 2sec, (c) background frame at 8sec, (d) background frame at 16sec.

After detecting the moving region of the input image, morphological operations such as delusion and illusion are deployed on the frame to reduce noise introduced by the foreground detection process.

III. Experimental Results

In this section, we compare performance of the proposed

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algorithm with that of traditional background subtraction and temporal difference algorithms in two major tasks. The experiments are conducted on real-time video sequences. The first experiment is done to evaluate the performance of the three algorithms in detecting a moving object, when the stationary part of the background image is dynamically changed. The second one is conducted to detect the stopped objects in the scene.

The quality of moving object detections is examined visually. The output image is displayed in binary form since it can clarify the performance differences among these methods. In the experiments presented below, most of the following parameters are fixed; the kernel size used in the median filter is 3x3 and the critical number of detected pixels per frame (CDP_{num}) is set to 60% of the total number of pixels in the given frame. We set the maximum duration of stopped state (SS) to be 2 seconds.

A. Detecting Moving Objects When the Stationary Parts of Background Image are Changed

To evaluate the performance of each algorithm on significant background changes, we have chosen a situation that has a displacement in the stationary part of the background image. For all methods, the first frame of video sequence has taken to be an initial background frame. In the proposed algorithm, the background image is initialized by the first frame of the input video sequence, and then the background image is gradually updated by pixel-wise and frame-wise status of the incoming frame.

The gradual updating of the background image is described in Fig. 2. The first image (a) is the first frame of the input video sequence. The three people in the image are considered as the stationary part of the background image. In fact, they were not standing in that particular position. At the beginning, the proposed algorithm can detect the three persons as they are standing in that particular position. However, in few seconds with the pixel-wise background updating, the background image is updated as shown in (b). The third image (c) shows a situation of updating the background image when the object is stopped at the scene for a longer period than the predefined duration of stopped state. Followed by the same procedure, updating of background image is continued as described in (d). In temporal difference technique the most recent frame is taken as a reference for the current frame. In the experiment of moving object detection when there are changes in the background, both the proposed algorithm and temporal difference relatively perform well.

The results of all the three approaches in this experimental setup are shown in Fig. 3. In the proposed algorithm because the first frame of video is taken by the background image and moving objects in that frame are considered to be stationary in the image, it detects some false positives for the first few seconds in the scene as shown in the right column of Fig. 3 (d). However, by dynamically updating the background image, the algorithm avoids further detection of these false positive regions as it can be seen in the left column of (d). The area detected as false positive is indicated by a red bounding box in the output images.

(a)
(b)
(c)
(d)

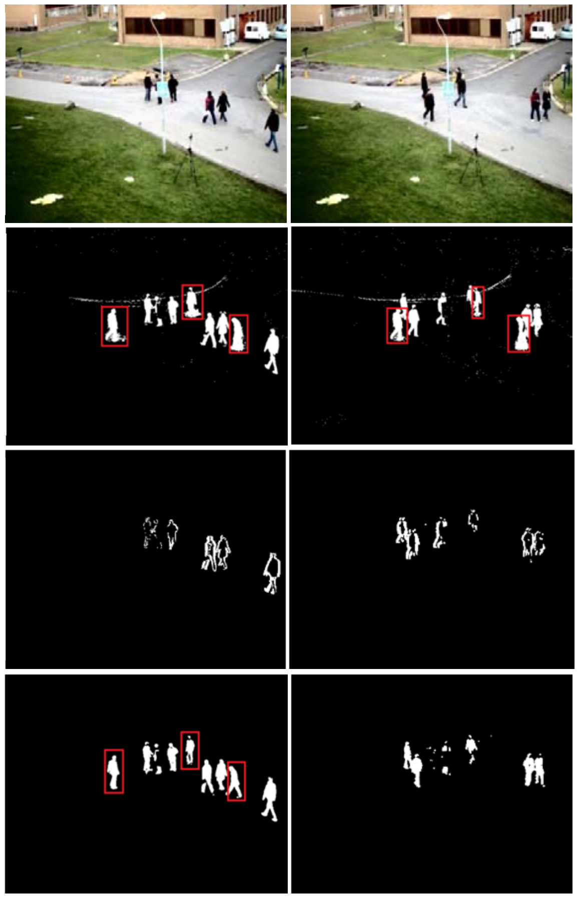

Fig. 3 The obtained binary result of the three approaches when the stationary part of the background is displaced, in which the right column and left column represent frames 25 and 200 respectively: (a) input frame, (b) background subtraction, (c) temporal difference, (d) the proposed method.

As being compared with the proposed method, traditional background subtraction continuously detects these false positive regions, which are not present on the real video as it can be seen on the bottom row Fig. 3 (b). The temporal difference performs well on avoiding of detecting false positive regions as shown in Fig. 3 (c). However, it cannot extract all relevant pixels of moving objects. Therefore, as we can examine visually, the proposed algorithm can avoid detecting false positives in a very few seconds as well as extracts most of the relevant pixels.

B. Detecting Stopped and Slowly Moving Objects

Here we want to evaluate the performance of each approach, when the object is slowly moving or stopped at the scene. It is assumed that the speed of the given object in real time is less than the frame rate.

Both the proposed algorithm and the background subtraction perform well in this regard. Here we need to detect the given stopped object only for the predefined duration.

The typical results of each algorithm are described in Fig. 4. The second row in the figure illustrates the results of traditional background subtraction methods. Although the output false positives do exist, it successfully detects the stopped objects in the scene. As shown in the third row of the Fig. 4, the results of temporal difference are quite poor at detecting stopped or slowly moving objects in the scene. The number of people detected by the temporal difference is less than that of input frames. The last row shows the result of the proposed algorithm. As shown in the figure, the proposed method can detect the slowly moving or stopped objects in the scene.

As we can visually confirm from the output images, the proposed algorithm performs better than the other techniques in the aspects of detecting the moving object in various situations as well as extracting of relevant pixels of the detected object.

(a)
(b)
(c)
(d)

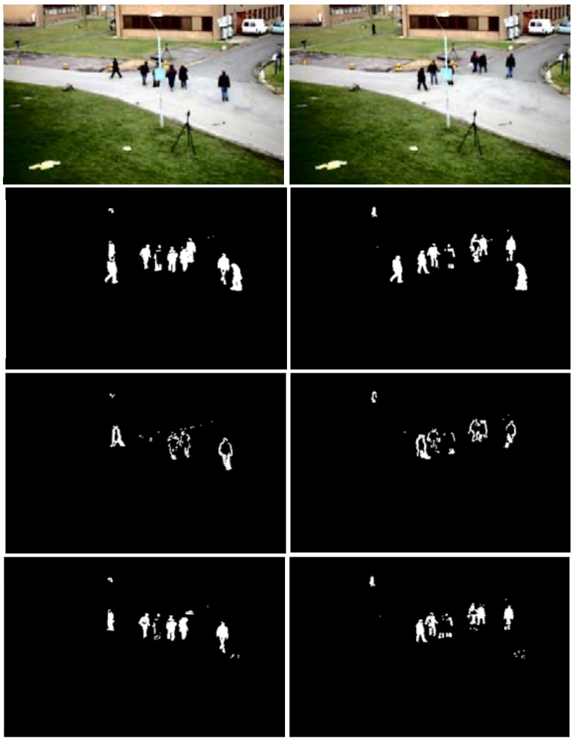

Fig. 4 Results of the stopped and slowly moving objects when comparing the proposed scheme and other methods: (a) input frame 80 and 115 from left to right respectively, (b) traditional background subtraction, (c) temporal difference, (d) the proposed method

IV. Conclusion

In this paper, we have presented a dynamic background updating algorithm for lightweight moving object detection. In order to reduce the effect of illumination change and noise in the image, histogram equalization and median filter have been employed respectively, followed by adaptive background subtraction and temporal difference of each frame. In parallel the dynamic pixel-wise and frame-wise background updates are exploited. Finally, morphological operations are applied to enhance the foreground image. Experimental results show that the proposed algorithm can address the noted problems of traditional background subtraction and temporal difference methods and performs much better than both approaches.

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References

[1] K. A. Joshi, and D. G. Thakore, "A survey on moving object detection and tracking in video surveillance system", *International Journal of Soft Computing and Engineering*, vol. 2, no 3, pp. 44-48, July 2012.

[2] A. M. McIvor, "Background subtraction techniques." *Proc. of Image and Vision Computing*, vol. 4, pp. 3099-3104, 2000.

[3] A. Elgammal, R. Duraiswami, D. Harwood, and L. S. Davis, "Background and foreground modeling using nonparametric kernel density estimation for visual surveillance", *Proc. of the IEEE*, vol. 90, no. 7, pp. 1151-1163, July 2002.

[4] S. Y. Elhabian, K. M. El-Sayed, and S. H. Ahmed, "Moving object detection in spatial domain using background removal techniques-state-of-art", *Recent Patents on Computer Science*, vol. 1, no. 1, pp. 32-54, Jan. 2008.

[5] J. Heikkilä, and O. Silvén, "A real-time system for monitoring of cyclists and pedestrians", *Image and Vision Computing*, vol. 22, no 7, pp. 563-570, July 2004.

[6] I. Haritaoglu, D. Harwood, and L. S. Davis, "W^4: Real-time surveillance of people and their activities", *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 22, no. 8, pp. 809-830, Aug. 2000.

[7] A. J. Lipton, H. Fujiyoshi, and R. S. Patil, "Moving target classification and tracking from real-time video", *Proc., Fourth IEEE Workshop on Applications of Computer Vision,* pp. 8-14, Oct. 1998.

[8] L. Wang, W. Hu, and T. Tan., "Recent developments in human motion analysis", *Pattern Recognition*, vol. 36, no 3, pp. 585-601, Mar. 2003.

[9] N. Paragios, and R. Deriche, "Geodesic active contours and level sets for the detection and tracking of moving objects", *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 22, no. 3, pp. 266-280, Mar. 2000.

[10] S. C. Zhu, and A. Yuille, "Region competition: Unifying snakes, region growing, and Bayes/MDL for multiband image segmentation", *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 18, no. 9, pp. 884-900, Sep. 1996.

[11] L. Wixson, "Detecting salient motion by accumulating directionally-consistent flow", *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 22, no. 8, pp. 774-780, Aug. 2000.

[12] R. Pless, T. Brodsky, and Y. Aloimonos, "Detecting independent motion: The statistics of temporal continuity", *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 22, no. 8, pp. 768-773, Aug. 2000.