Illegal Vehicle Parking Detection Based on Online Learning

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ABSTRACT: *In this paper, it is proposed an improved method to aim at the illumination vary problem for detecting illegal parking in the surveillance video. The method uses a frame to frame subtraction method for modeling the background, and update it, then using the background subtraction method to get the moving candidates, it can obtain the accurately moving objects after appropriate processing. At the same time, the work also used a method based on texture and color histogram. Besides, in order to detect the salient object, we propose a novel adaptive feature combination mechanism to combine the different features, in which the combining weight of each static map is learned using online learning. At last, it justifies whether the vehicles are parked illegally or not. Experiment results demonstrate that the proposed method significantly outperforms the other state-of-the-art methods, and it is more suitable for the real scenes.*

Keywords: Moving Target Detection, Salient Object Detection, Online Learning, Illegal Parking Detection

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1. Introduction

With the development and application of image processing and computer vision in intelligent video surveillance, target tracking and detection technology becomes more mature. The number of motor vehicles continued to climb and traffic violations increased at the same time. The intelligent video surveillance technology owns unique and it has gained more and more attention. However, there are still many problems in the use of this technology.

Methods for solving the illumination variance commonly used are [1], [2] and so on. Using the background gray image, the average gray value is subtracted from the normalized value, where the method is simple and easy to completed, but not suitable for uneven illumination conditions, and local updating background scene. There are also some operators, such as the use of SIFT operator which is not sensitive to illumination variance to solve this problem.

In this paper, we proposed a multi-scale framework to solve the problem above: firstly, we use a frame-to-frame subtraction to get the background frame [3]; then we use the present frame to subtract the background to get the foreground frame and get the reliable moving object after some processing algorithm. If there is no object in the detection region, we put forward the salient object detection method based on LBP (Local Binary Patterns) texture and color histogram [4], and the weights are based on online learning. Using the image segmentation method to get the salient object, we finally devise the strategy to detect whether the vehicle is parked illegally or not. Detailed algorithm process is as shown in Figure 1.

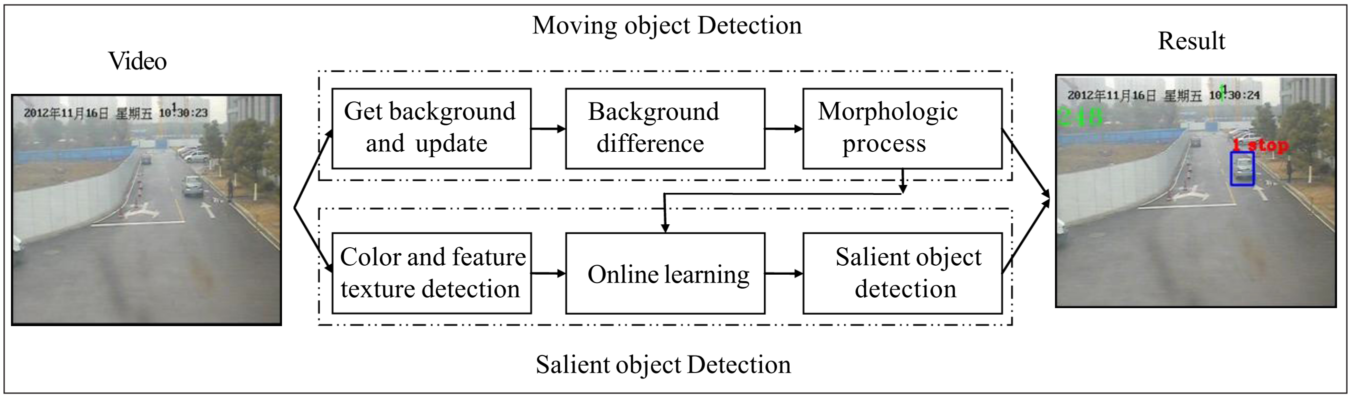

Figure 1. The flowchart of the proposed method

2. Detection for Moving Object

2.1 Frame-to-frame subtraction

We put forward a method that is frame-to-frame subtraction among every three frames, for the pixels of background area, if the gray value varies very little or no change within a period of time and hence we can consider it as background pixel. Set the background as B, f_k for every frame image. So the frame difference results:

$$\Delta f = | f_k - f_{k+3} | \tag{1}$$

Then through the appropriate threshold, after some image processing such as binaryzation and image smoothing, count the number of "255" pixels from the results of formula (1). When the number is below the threshold, it means the present frame almost has no change, finally the background is obtined.

2.2 Background renewal and background difference

Actually, as the illumination variation, the background is in constant change, so the adaptive background updating is necessary. The paper put forward on no-motion region update, from the statistics of background in the region detected, only for the pixels of background in a certain period of time can update. The update process is as follows:

$$f_b'(x, y) = f_b(x, y) + (1 - \alpha) f_k(x, y) \tag{2}$$

$f_b'(x, y)$ is the renewal background frame, $f_b(x, y)$ is the background frame before update and α is the renewal rate. From the statistics of online learning, set it as 0.2, as shown in figure 2, and get the new background. So we can get the reliable foreground with the background difference.

2.3 Morphological process

Due to the presence of noise pixels and problems caused by window cavity [5], it is necessary to do image morphologic processing. Firstly, by open operation that is corrosion first and then is by expansion. Set the structural elements E, the present binary image P_r, t and hen the open operation results R:

$$R = (p_r \otimes E) \oplus E \tag{3}$$

It can remove the most of noise targets, then though the use of closing operation, we can make the target more complete. The closed operation results R:

$$R = (p_r \oplus E) \otimes E \tag{4}$$

So the moving vehicle targets can be detected accurately, where the effect is as shown in Figure 3.

3. Salient Object Detection

3.1 Texture feature

The texture feature of a salient target is obviously different from its surroundings [6]. It can detect it based on these "*special*" pixels. Firstly, pay segmentation into $\{S_1, S_2 \ldots S_k\}$ from the original image frames, so every frame image can be represented from these segmentations. For each segment of S, we will do expansion processing firstly and then to expand into a larger area of the S':

Figure 2.Background after online learning

Figure 3. Detection of the moving vehicle (Frame for No.142,144,146,178)

$$S' = \frac{\sqrt{5}-1}{2} \times \frac{height + width}{2} \tag{5}$$

The height and width as the segmentation map's height and width, and the region R is the result of difference of S and S'. This texture operator using the LBP operator, namely the local value of two models, the biggest advantage is that the illumination invariance. The S and R are under LBP operator processing, the feature vector is obtained for V_s and V_R, the two histogram distance is:

$$\chi^2 (S, R) = \frac{1}{2} \sum_j \frac{(f_s(j) - f_R(j))^2}{f_s(j) + f_R(j)} \tag{6}$$

This it is one of the conditions of salient image segmentation. For the rest of the segment S, do the same operation.

3.2 Color feature

Distribution map of color space is first used in [7] which is applied to detect salient objects. Later it is used to detect and its performance has improved. The principle is that more widely is distributed color in the image, the less possible it contains this color. Of course, the premise is that this kind of a salient target must have the obviously discrimination from the background image, or the feature's effect is not very well [8].

Firstly, for each segmentation image, set color space conversion from RGB image into HIS image. A large number of experimental results show that RGB space is superior to the HIS space for color feature. Count for H, S and I components for the histogram, then the rest of all segmentation blocks for the same operation, at last, make all feature histogram into a histogram of the pixels, so the salient object is obviously different from its surroundings. It is easily can be separated as show in Figure 4:

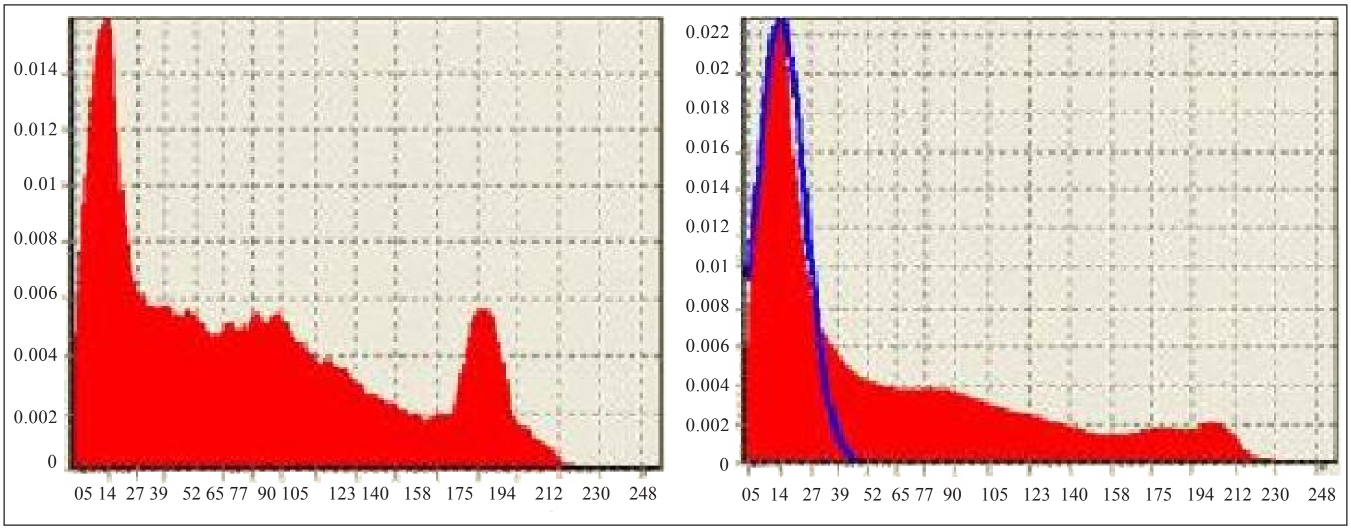

Figure 4. Statistical color histogram (left) and Salient segmentation from histogram (right)

3.3 Multi-scale feature and online learning detection

According to the texture and color features for the above, this paper put forward a multi-scale feature detection method to detect the salient objects, thus it is the key for solving the linear adaptive weight. Assumption for the access to K feature map, the prior weight values for $F = \{f_1, f_2 \ldots, f_k\}$, we use the online learning method to update the weights of these characteristics, in order to achieve the optimal solution. The online learing method use is more efficient and faster, while reducing the part parameters.

The online learning approach in this paper is: firstly, saving the moving target detected by above algorithm, normalized into a pixel size of 30×30, as shown in the Figure 5; then extract the target by texture and color feature, set initial weights $F = \{0.5, 0.5\}$. In the absence of moving objects in the video frames, we need to compare with the models from moving target by calculate the texture and color features of the whole frame. Finally, by gragh cut, get the salient target. Compared with the original models, if the characteristic function value in the certain range of threshold values, it can update the new target's characteristic function into the original functions and update the weights at the same time; else abandon it.

According to comtinous learning, each weight update for $f_i^* = f_{i-1} + af_i$, where a is the learning coefficient. Through a large number of data statistics, get the optimal weights of these feature vectors in the detection of salient target. For the purposes of this article, the texture features and color feature $F1$ and $F2$, can be accuatedly segamented from the salient target. We use 2000 image which contains vechicle for learning, the optimal weights finally after learning the value of $F = \{0.53, 0.47\}$. Results are shown in Figure 6.

4. Experiment and Results

According to the above algorithm, it can detect the moving and salient vehicles by the strategy whether the vehicle is illegally parked or not. In the detection region, record the trajectory of moving vehicles. If the vehicle's position does not change or change a little in a certain period of time, such as 100 frames, the algorithm can determine the vehicle is illegally parked. For the salient image, detect it with the features above and find the target, then pay segmentation. At last, with the two cases above, marked the target by blue rectangle, as shown in Figure 7, and send the alarm information (alarm time, alarm camera, the picture with illegal vehicles) into monitoring center.

Figure 5. Normalized the target models (positive)

Figure 6. Original image (left), the binary image of salient object (right)

To evaluate our method and compare it with existing methods, select the same video and pictures. By the recall rate (Recall), the accuracy rate (Precision), comprehensive evaluation index (F1-Meature) is compared with the previous algorithms. Precision means that rate of accurate rate refers to be detected information. Recall means the rate refers to the ratio of all the correct information detected, so

$$Precison = \frac{TP}{TP + FP} \tag{7}$$

$$Recall = \frac{TP}{TP + FP} \tag{8}$$

A true positive (TP) means the testing pixel which is labeled as a salient target pixel and is correctly detected as a salient target, a false positive (FP) stands for the pixel is not labeled as a salient target pixel but is detected as salient targets, and so on. Accuracy the salient targets detection is used and then it is evaluated by calculating the detection rate ($DR = TP / (TP + FN)$) and the false alarm rate ($FAR = FP / (TP + FP)$). Higher DR means the salient targets can be detected more correctly, while lower FAR shows the background frame will not be misclassified as salient targets. A good detection algorithm is to make a compromise between DR and FAR since higher DR usually results in higher FAR and vice versa.

In all, the condition of the result of salient object detection is shown in Table 1.

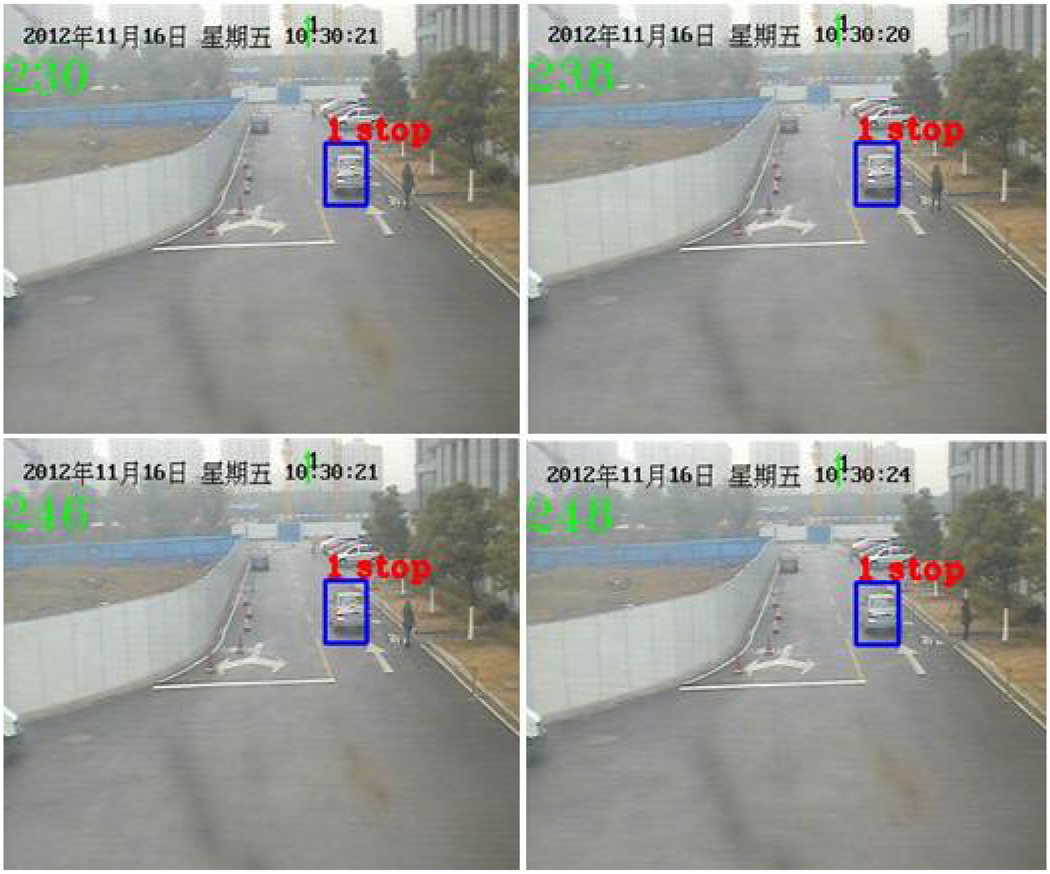

Figure 7. Detection of illegal parking (Frame for No.230, 238, 246, 248)

		Labeled salient object	
		1	0
Detection result	TURE	*TP*	*FP*
	FALSE	*FN*	*TN*

Table 1. Results of the Salient object detection

The $F1$-measure is that:

$$F1 = \frac{(\alpha^2 + 1)\, P * R}{\alpha^2 (P + R)} \tag{9}$$

α is always set as 1.

Due to the illumination and other scene change, the moving target and salient object tracking and detection's results are poor in the previous algorithm. Especially, the result is very poor, when the foreground and background is similar, as showed in the Figure 8. The first row shows that people may be mistaken for detecting a vehicle, as shown in Figure 8 of the second and third rows.

Compared with methods [3] and [7], the algorithm proposed in this paper can effectively reduce the false positives in the illumination variance environment and foreground and background similar with each other. As shown in the Figure 9, the algorithm can distinguish the background and foreground object detection and reduce the non vehicle for vehicle probability, so as to effectively reduce false positives.

Figure 8. Failure object detection

Figure 9. Non vehicle (people or nothing) is not detected

So we get the Table 2 as followed:

	Method [3]	Method [7]	Poposed
Recall	0.68	0.79	0.80
Precision	0.31	0.69	0.79
*F*1	0.53	0.74	0.79

Table 2. Recall and Precision results

5. Conclusion

In this paper, we proposed a multi-scale algorithm for detecting the illegal parking for the surveillance video of an industrial park. The algorithm used the Open computer source in the VS2010 integrated development environment with Pentium 3.0HZ and 3GB memory PC. Compared with the previous algorithm, it has more real-time and robustness. Besides, the online learning method can reduce manual setting parameters, but it requires a large amount of data for training and classification. The online learning is still the key to point the difficulty of future research. This paper only used two kind of feature detection, but the framework facilitates the follow-up to add new features to detect. So the feature characteristics component serves as a direction for future research.

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