Moving vehicle detection algorithm based on motion edge extractor

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Abstract

In this letter, we propose a moving vehicle detection method based on motion edge extractor (MEE). In the course of the vehicle detection, the motion and contour information are prominent, so we combine them together to extract the moving objects with complete contours. We first modify the Gaussian Mixture Model (GMM) to estimate the background more precisely. Then an object extraction method in static image is proposed. The original image and the background image go through the object extraction method and a series of logical operations to get the moving areas. At last we apply a simple filling method to refine the result and accurately extract the vehicle areas. The experiment result shows that our algorithm is not sensitive to illumination and can detect the vehicles with similar colour to the road robustly.

Keywords: vehicle detection, motion edge extractor, video monitoring

1 Introduction

With the rapid development of technology, the Intelligent Transportation System (ITS) becomes increasingly important, and the vehicle detection in image sequence becomes a hot subject of research. The traditional object detection methods have been studied for a long time. The frame differencing method is simple but has a high false detection rate. The optical flow method is able to deal with the movement of the camera but requires special hardware and large computational complexity. The background subtraction method is able to get the moving objects but sensitive to the sudden change of movement and illumination.

Among the traditional methods, the Gaussian Mixture Model method [1] is widely used to extract the foreground. This method works when the camera is fixed and it is robust to slight disturbance of the camera. But the GMM method has low convergence speed, which will affects the accuracy of the background modelling. It is also sensitive to global change. Many researchers have tried to modify the GMM method [2-4], Zoran [4] combines the GMM and frame differencing method together to solve the problem of multi-modal distribution of pixels and overcomes the influence of the illumination changes and other factors such as shaking branches. However, due to the low update rate, an object moving slowly will be considered as background and produce “ghosting” in the detection result. For the object with similar colour to the background, all of the above methods cannot extract the complete objects.

Recently some new methods have been proposed. Ye Li [5] presents a vehicle detection algorithm based on template matching which can effectually detect the cars in congested traffic, but this method is slow due to the matching procedure. Mithun [6] applies a method based on multiple virtual detection lines (MVDL) and time-spatial images (TSI) to detect the vehicles, this method is fast and accurate, but it is dependent on the placement of the camera and it will fail if a vehicle changes its lane. Bingfei Wu [7] applies different kinds of background modelling algorithm according to the traffic condition. And they apply sobel detector to optimize the detection result to get accurate result in the heavy traffic. This method relies on the placement of the camera and does not work fine when it is dim. Vargas [8] tries a Sigma-Delta background estimation method based on confidence measurement to sense the traffic condition and adjust the update rate of the model. This algorithm is efficient and is able to deal with the congested traffic. But when there are vehicles with similar colour to the road, the algorithm cannot extract the vehicle correctly. Jie Zhou [9] applies prior knowledge and SVM classifier to modify the moving objects detection. The algorithm is robust to different weather and illumination conditions, but for each image sequence, the user has to set many parameters manually. Zezhi Chen [10] proposes a self-adapted Gaussian Mixture Model to extract the moving vehicles. The level set method is applied to refine the result. This algorithm works well in different weather and illumination conditions but it can only deal with the vehicles heading for the same direction. Ye Li [11] presents a detection algorithm based on And-Or Graph to detect vehicles in congested traffic. But this algorithm requires each kind of vehicle to be trained and it cannot detect the side-view vehicles.

The contour and movement information are the most prominent features of the vehicle in the video. Considering

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only the movement of the vehicle, current algorithms require different parameters according to different conditions and they cannot get the complete contours of the moving vehicles. If we only consider the contour, it is hard to distinguish between the vehicles and other static objects. So we combine these two features together and propose a novel moving vehicle detection method based on motion edge extractor (MEE). We first modify the Gaussian Mixture Model (GMM) to model the background more precisely. And SVM is applied to cope with the "ghosting" problem. Then we find the contour profile of the connected area from the edge graph extracted by the phase congruency method. And we expand the internal and external contour to get the complete target area based on static image. Both of the original image and the background image go through the complete object extraction method and a series of logical operation to get the moving areas. We then eliminate the shadow in the YCrCb colour space [15]. At last we apply median filter and several steps of morphological operations to extract the accurate and complete moving objects. Our algorithm is able to cope with the vehicles that have similar colour to the background and it is not sensitive to illumination.

2 The proposed motion edge extractor algorithm

The Motion edge extractor (MEE) algorithm includes four parts: the improvement of the GMM, the complete object extraction from static image, the moving area extraction and patching the undetected area. Please see Figure 1.

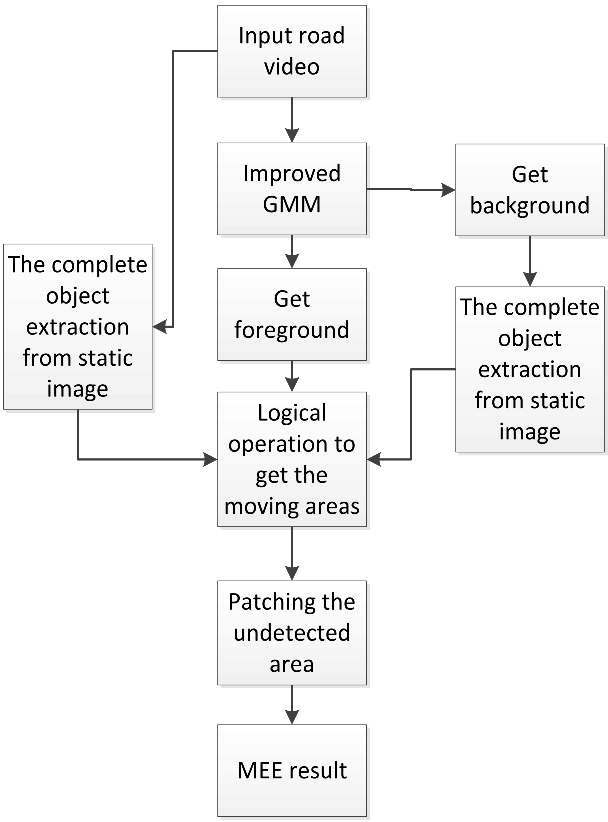


FIGURE 1 MEE flowchart

2.1 IMPROVED GAUSSIAN MIXTYRE MODEL TO GET MORE ACCURATE BACKGROUND

The traditional GMM method uses K Gaussian distributions to model each pixel. For a new frame, the matching with the K Gaussian distributions is done pixel by pixel, and the parameters of the first matched distribution are updated as [1].

$$\Omega_{n,t+1}=(1-\alpha)\cdot\omega_{n,t}+\alpha\,, \tag{1}$$

$$\mu_{n,t+1}=\left(1-\alpha/\omega_{n,t+1}\right)\cdot\mu_{n,t}+\alpha/\omega_{n,t+1}\cdot X_{t+1}\,, \tag{2}$$

$$\sigma^2_{n,t+1}=\left(1-\alpha/\omega_{n,t+1}\right)\cdot\sigma^2_{n,t}+\alpha/\omega_{n,t+1}\cdot\beta\,, \tag{3}$$

$$\beta=\left(X_{t+1}-\mu_{n,t+1}\right)^{\mathrm{T}}\cdot\left(X_{t+1}-\mu_{n,t+1}\right)^{\mathrm{T}}. \tag{4}$$

Parameters of the unmatched distribution are updated as Equation (5).

$$\omega_{n,t+1}=(1-\alpha)\cdot\omega_{n,t}\,, \tag{5}$$

$\omega_{i,t}$ denotes the weight of the *nth* Gaussian model at time *t*, and it satisfies $0\le\omega_{i,t}\le1$, $\sum_{i=1}^{K}\omega_{i,t}=1$. $\mu_{i,t}$ and $\sum_{i,t}$ denotes the median vector and covariance matrix of the i^{th} Gaussian model at time *t* respectively, we have $\sum_{i,t}=\mu^2_{i,t}I$. I is an identity matrix and α is the update rate defined by the user, it satisfies $0\le\alpha\le1$. The update rate increases when α gets larger. Since the Gaussian Mixture Model updates the whole image, if the update rate is too small, it will produce "ghosting" and it will become sensitive to the change of illumination and the shake of camera. If the update rate is too large, the slowly moving vehicles will be treated as the background.

In order to solve this problem, we introduce an update parameter N and the update rate becomes Equation (6) and Equation (7).

$$\alpha=\alpha\cdot\mathrm{N}\,, \tag{6}$$

$$\mathrm{N}=\begin{cases}1 & \text{when the pixel is background}\\ 0 & \text{when the pixel is foreground}\end{cases}. \tag{7}$$

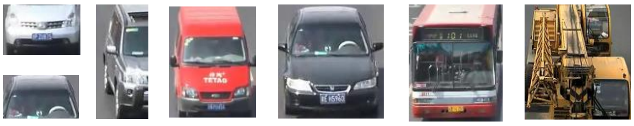
From the above equations we know that according to the detection result of the previous frame, the background update rate in the moving region is set to zero. So the algorithm is able to detect the slowly moving vehicles when the update rate is very large.

a. Input Image b. Extracted Background Based On Tradition GMM c. Extracted Background Based On Improved GMM

FIGURE 2 Improved GMM

The method in Figure 2c is able get a more precise background image. But when there are vehicles in the first frame of the video, the GMM will set the whole image with the vehicles as the background. It will have large impact on the moving area detection and lead to failure. So when we deal with the first frame of the video, we apply HOG and support vector machine to scan the frame [12]. The detector windows tile with a grid of overlapping blocks in which HOG feature vectors are extracted. And it scans across the image at all positions and scales. The result is noted by *S*. For the background, $S=1$, and for the vehicle, $S=0$. Since the gradient directions of the road and vehicle are quite different, the result is very accurate. We use SVM to classify one hundred images and the road detection rate is up to 100%, the vehicle detection rate is 93%, just only a few trees are taken as vehicles. Figure 3 shows some of the SVM training set.

Positive class



Negative class

FIGURE 3 SVM training set

We modify the Equation (6) according to the result of SVM.

$$\alpha=\begin{cases}\beta & S=1\ \&\ \text{frame}<50\\ \alpha & S=0\ \&\ \text{frame}<50\,.\\ & \alpha\cdot N \quad \text{others}\end{cases} \tag{8}$$

In the first frame where there are vehicles, the first 50 frames update rate is set to β ($\beta \gg \alpha$) while the update rate of the rest keeps unchanged. With a high update rate we can eliminate the “ghosting” fast.

Figure 4 shows the background extracted at the 20th frame. Figure 4a and 4b denote the traditional GMM’s result and the modified GMM’s result respectively. The result shows that applying SVM to modify the update rate of the GMM is able to cope with the “ghosting” problem.

a Result Before Improvement b Result After Changing Update Rate According to SVM

FIGURE 4 Comparison figure of the results for the modified GMM and traditional GMM

2.2 COMPLETE OBJECT EXTRACTION FROM STATIC IMAGE

The phase congruency (PC) uses the most consistent phase in Fourier components as the feature point. It fits the human visual system and it is robust to the change of illumination [13].

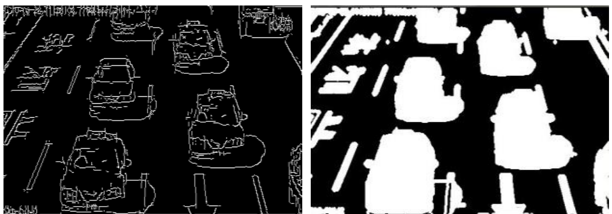
Phase congruency does not make any assumptions of the waveform. It finds feature points according to the consistency of the phase. Peter Kovesi [14] developed a modified measure consisting of the cosine minus the magnitude of the sine of the phase deviation and it incorporates noise compensation. The modified function will provide more local responses. Please see Equation (9) and Equation (10).

$$PC(x)=\frac{\sum_n W(x)\lfloor A_n(x)(\cos\delta-|\sin\delta|)-T\rfloor}{\sum_n A_n(x)+\varepsilon}\,. \tag{9}$$

$$\delta=\Phi_n(x)-\overline{\Phi}(x)\,. \tag{10}$$

A_n denotes the amplitude of the scale *n*, $\Phi_n(x)$ is the phase value of the nth Fourier component at *x*, The weighted mean phase angle is given by $\overline{\Phi}(x)$. The term $W(x)$ is a factor that weights for frequency spread. A small constant ε is incorporated to avoid division by zero. Only energy values that exceed T , the estimated noise influence, are counted in the result. The symbols $\lfloor\ \rfloor$ denote that the enclosed quantity is equal to itself when its value is positive, and zero otherwise.

Then combine phase congruency information over many orientations by using Gabor wavelets [8]. We can obtain the edge information of the image. Please see Figure 5.



a edge information extracted by PC b complete object extraction from static image

FIGURE 5 The results of complete object extraction from static image

Due to the discontinuity of the vehicle contour extracted by PC, it is hard to calculate the final motion area. We scan the image row by row to find the first unmarked point and mark it, then check if its eight neighbour points are connected and unmarked, if a neighbour is unmarked and forms a connected area with it, mark that point as seed point. This process is done recursively until the whole connected area is marked. Using this method we can mark all the connected area in the image.

Next the inner and outer contours of the connected areas were redrawn, the dilation operation is done. Thus the connected areas with continuous contours are obtained. Please see Figure 6. At last, all the connected area goes through the connecting and filling operation to produce the complete area. Please see Figure 5b.

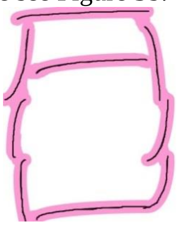


FIGURE 6 Sketch map of discontinuous contour connection

This method is able to extract complete object area from a static image and it is robust to illumination change.

2.3 MOVING AREA EXTRACTION

Since the complete object extraction algorithm is able to extract complete object area and it's robust to the illumination and contrast change, we combine it with the GMM to effectual extract the motion area. The original frame (Figure 2a) and the background produced by the improved GMM (Figure 2c) go through step B. Then we combine the result and the foreground extracted by GMM to go through a series of logical operations to obtain the complete motion area. Please see Figure 7.

We apply the method in step B to process the original frame and the background image and obtain two images as Figure 8a and Figure 8b.

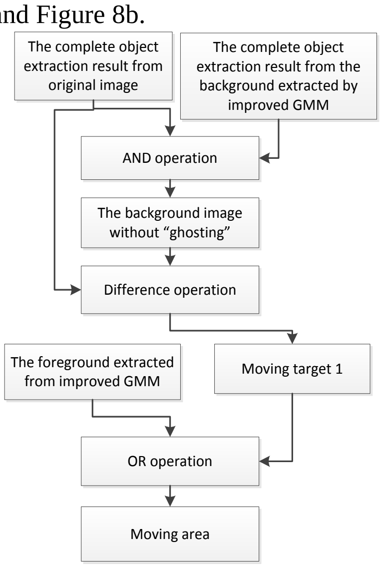


FIGURE 7 Flowchart of the motion area extraction algorithm

Let $f_1(x,y)$ denote the original frame processed by step B, $f_2(x,y)$ denote the background image processed by step B. The final motion area $f_3(x,y)$ can be calculated as follow.

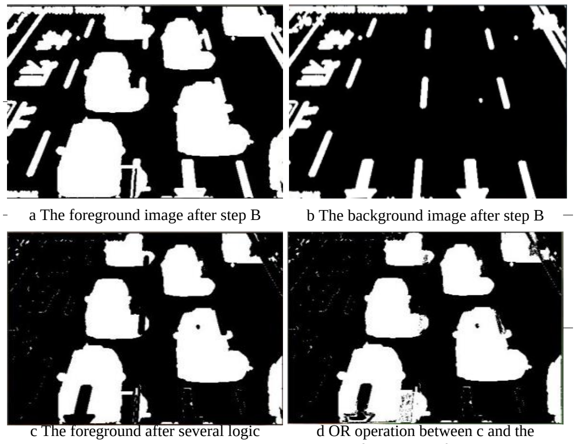
$$f_3(x,y)=f_1(x,y)-\left[f_1(x,y)\cap f_2(x,y)\right] \tag{11}$$

$f_3(x,y)$ is the moving object areas showed in Figure 8c. In order to avoid the influence of the "ghosting" in $f_2(x,y)$, we do not just apply difference operation between $f_1(x,y)$ and $f_2(x,y)$. If there exists "ghosting" in background image, part of the foreground in $f_1(x,y)$ will be mistaken as the background. We apply difference operation between $f_1(x,y)$ and the sum of $f_1(x,y)$ and $f_2(x,y)$ to improve the accuracy of detection.

Since there is an overlap between the pavement line and the vehicle in the image, the result of the difference operation may have some incomplete areas. Since the foreground image extracted by the improved GMM will not be influenced by the pavement marking line, we apply OR operation to the foreground from improved GMM (denoted as $f_4(x,y)$) and $f_3(x,y)$ to obtain the more complete moving areas denoted as $f_5(x,y)$.

$$f_5(x,y)=f_3(x,y)\cup f_4(x,y) \tag{12}$$

The final result is shown in Figure 8d.



a The foreground image after step B
b The background image after step B
c The foreground after several logic operations
d OR operation between c and the foreground of GMM

FIGURE 8 The extraction of the moving area

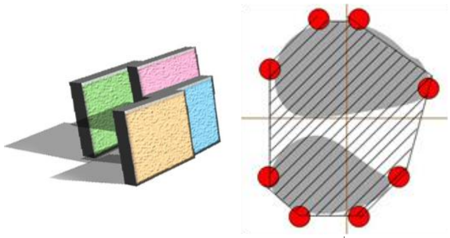
2.4 PATCHING THE UNDETECTED AREA

Figure 8c, 8d show that when the moving target overlaps the marking line, the final moving areas extracted will have some holes similar to the marking line. Although the OR operation between the moving object and the foreground of GMM will patch part of them, we still have to patch the undetected areas since it's hard to get full object from GMM model. So we should do the patching the undetected area operation.

Undetected region patching algorithm is as follows.

Firstly, we traverse the image with a rectangular window (10·8 in our experiment), if more than 35% of the pixels in the window are valid, go to next step, else keep traversal. In the process of moving the window, there is overlap between two consecutive windows to help patch the holes. Please see Figure 9a.

Secondly, divide that region into four parts, and for each part we find 2 outer points. Then connect these eight points to obtain a closed contour and set the area within the contour as valid. It can guarantee not extend the contour. Please see Figure 9b.



a The foreground image after step B　　b Find and fill the contour

FIGURE 9 Patching the undetected area sketch map

This method is able to not only patch the undetected area but also keep the shape of the area. After patching the undetected area, the moving area (Figure 8d) is shown in Figure 10.

FIGURE 10 Result of the patching

3 Post processing

There exist shadows in the video due to the illumination, the shadows move with the vehicles and they are detected as the moving object too. The shadows affect the accuracy of the vehicle detection.

In YCrCb colour space, luminance and chrominance signals are independent. The YCrCb colour space is robust to brightly light backgrounds, Kumar [15] also confirms that YCrCb is the best colour space for shadow detection, so in this paper YCrCb colour space is used to eliminate the shadows.

After eliminating the shadows, we apply median filter and several morphological operations to obtain the accurate and complete moving objects.

FIGURE 11 The accurate and complete moving objects

4 Experiment results

The performance of the proposed method will be demonstrated in this section. Experiments are conducted on a computer with Intel(R) Core(TM)i5-2450M CPU @ 2.50 GHz 4.00GB RAM. The coding is finished in Microsoft visual studio 2010 and opencv2.3.1.

In the experiments, the image sequences are extracted from different videos under the different conditions.

We test the algorithm in a cloudy weather (the first row of Figure 12), in situations where there are many dark-colour cars (the second row of Figure 12) and in situations where there are cars with similar colour to the road (the last row of Figure 12). The experiment result shows that under these three kinds of conditions, the MEE algorithm is able to extract the complete and accurate moving vehicles.

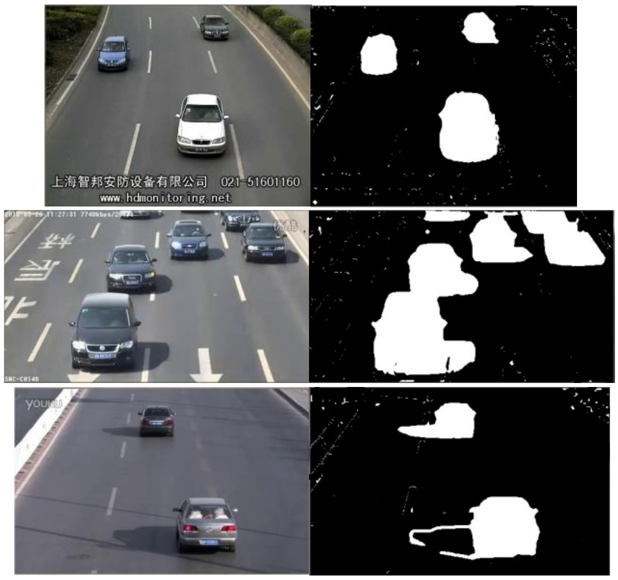
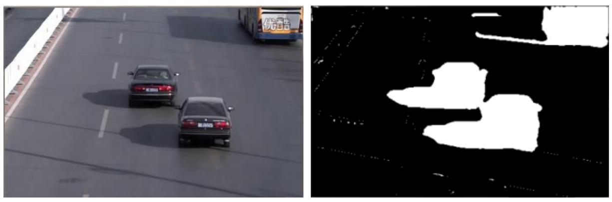
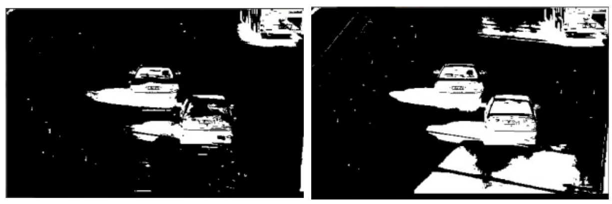


FIGURE 12 Vehicle detection results of the MEE algorithm proposed in this paper



a video image　　b result image of our algorithm

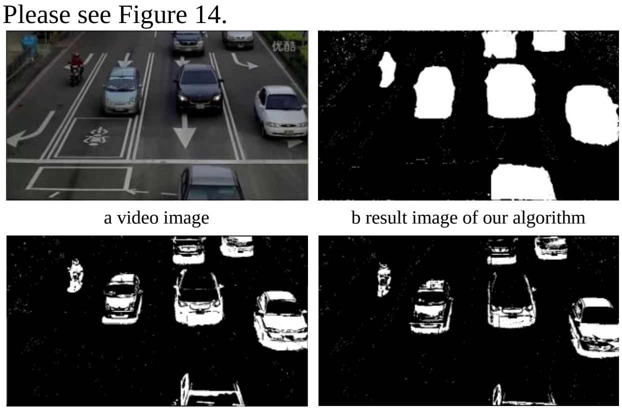


c result image one of [16] algorithm　　d result image two of [16] algorithm

FIGURE 13 Some comparison results of moving vehicle detection in videos where there exist “ghosting” and dark-colour cars

In Figure 13, we compared our method with the method in [16]. Li [16] uses frame difference method and GMM to extract the foreground image. This method can model the background fast and deal with the "ghosting". Please see Figure 13c. However this method still heavily relies on the parameters. When the background matching threshold is large, it is able to eliminate the "ghosting" quickly but it cannot correctly extract the vehicles with similar colour to the road. When the background matching threshold is small, it can extract the vehicles correctly, but it introduces in noises at the same time. When the "ghosting" exists, the disadvantage is more clearly. Please see Figure 13d. Our algorithm makes full use of the edge and motion information of the vehicles. It can cope with the "ghosting" and the cars with similar colour to the background. Please see Figure 13b.

At the start of the testing video, the illumination condition is good, but after about fifty frames, the illumination condition starts to get dark. Wu [7] applies different kinds of background modelling algorithm according to the traffic condition and uses sobel detector to optimize the detection result to get accurate result in the heavy traffic. Vargas [8] tries a Sigma-Delta background estimation method based on confidence measurement to sense the traffic condition and adjust the update rate of the model. This algorithm is efficient and is able to deal with the congested traffic. The above two algorithms cannot extract complete contours of the vehicles which have similar colour with the road when the illumination condition changes. Our algorithm makes full use of the edge and motion information to extract the complete vehicle contours and it's robust to Illumination change. Please see Figure 14.



a video image   b result image of our algorithm

c result image of [7] algorithm   d result image of [8] algorithm

FIGURE 14 Some comparison results of moving vehicle detection in real traffic video captured

5 Conclusions

In this paper motion edge extractor algorithm has been proposed. In this algorithm we have stimulated the human visual system and detected the moving objects by the movement of the objects and their edge information. The algorithm has been divided into four steps: First, we have improved the GMM to obtain a more accurate background. Second, we have expanded the object contour extracted by phase congruency strategy to obtain the complete targets. Then we have extracted the moving area using the background information. Finally, the missed areas have been repaired. Our algorithm has made use of the edge and motion information of the vehicles to accurately extract the vehicles. The experiment result has shown that the proposed algorithm is able to cope with the "ghosting" and the cars with similar colour to the background and it is robust to the illumination change.

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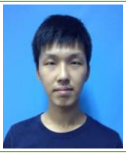

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