AN IMPROVEMENT OF REAL TIME CAR LICENSE PLATE DETECTION
IN THE SURVEILLANCE SYSTEM

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ABSTRACT

We improve RTCLPD (Real Time Car License Plate Detection) method for detecting more than one car license plate in an image. The moving object detection method is applied to recognize the number of cars in the image. We used a simple condition to filter out the moving object which is not a car. Some parameters are estimated by the obtained moving object and RTCLPD is applied in the partial area of each moving object. Since RTCLPD is applied in each moving object, it can be improved to detect more than one plate in an image. According to the results, we detect the car license plate accurately in a short time and all plates are detected in an image.

1. INTRODUCTION

In the most car surveillance systems, such as highway monitoring, parking control, etc., to recognize the car license number is a very important procedure. The car license number is used to match up the database for completing the automatic car surveillance system. In the recognition processes, CLPD (Car License Plate Detection) is the first and the essential procedure[1][2].

Many methods of CLPD are proposed. These methods work under prescribed conditions usually, such as limited speeds, fixed lightings and driveways. Some features of the car license plate are used for CLPD, such as corners[3], colors[4], symmetries[5] and edges[6]. The fuzzy logic and the neural networks[7][8] are artificial intelligence schemes. These methods are also used to detect the car license plate location. However, since these methods require large computational time and memory, they are not suitable for real time system.

RTCLPD (Real Time Car License Plate Detection) method[9] is proposed to detect the car license plate in the real time system. Since RTCLPD assumed that there is only one car license plate in an image, only one car license plate can be detected while two or more car license plates exist. If we know the number of cars in an image, we can detect each car license plate one by one. We can recognize the number of cars by the moving object detection method because the cars are the moving objects in the video. Hence, in the proposed, the moving object detection method is applied to improve RTCLPD.

One of the common moving object detection methods is the background subtraction[10]. Two of the basic processes in the background subtraction are suitable subtraction and background maintenance[11]. The background subtraction method needs a reference background image which is not including any moving object. Moving objects can be recognized by computing the differencing between the current image and the reference background image.

We applied the moving object detection method to improve RTCLPD scheme. In this paper, RTCLPD method is described first and the proposed method is shown. In the experimental results, we detect the car license plate accurately in a short time and all plates are detected in an image.

2. THE RTCPLPD METHOD

The flowchart of the RTCLPD method[9] is shown in Fig. 1. The color image (a frame of the video) is transformed to gray image. Then the binary edge information image is obtained by the first derivate in the horizontal direction and smooth thresholding. The rough regions of the car license plate are detected by the binary edge information image. The accurate car license plate regions are obtained by simple rules. Three conditions are applied to determine the real car license plate.

Since only one car license plate is assumed in an image, only one car license plate is detected whatever how many car license plates in an image. If we know how many cars in an image, we can detect all car license plates in the image.
3. THE PROPOSED METHOD

The flowchart of our proposed method is shown in Fig. 2.

We know how many cars in an image by moving object detection method. The simplest background subtraction method is applied to obtain the moving objects. The reference background image is updated when the moving object is not detected. If any one moving object is detected, the rough plate size is estimated by the ratio of the real car width to the real plate width for each moving object. After the rough plate size is obtained, the RTCLPD method is applied to detect each moving object. The RTCLPD is processed in the partial area of the moving objects for reducing computational time.

3.1. Input an image

The input images are color images and its size are 640 by 480 pixels. For save the computational time, we transform the color image into gray level image. An example color image is shown in Fig. 3.

![An image for detection is captured as a frame of the video.](image)

3.2. Extraction the moving objects

The moving objects are obtained by simple background subtraction method. In the background subtraction method, the reference background image must be obtained first. We compute the average of 30 frames which are not including any moving object to be the reference background image. We obtain the difference image, $f_d(x, y)$, as

$$f_d(x, y) = |f(x, y) - f_{bg}(x, y)|,$$  \hspace{1cm} (1)

where $f(x, y)$ is the gray value of $(x, y)$ in the current image and $f_{bg}(x, y)$ is the gray value of $(x, y)$ in the reference background image. If the $f_d(x, y)$ is larger than a threshold value, the pixel value at $(x, y)$ is 1. Otherwise, the pixel value at $(x, y)$ is 0. Therefore, the binary difference image is obtained.

Sometimes, there are many breaks in a moving object. Since the breaks are able to affect the accuracy of the moving object detection, the dilation and the erosion are applied. The 8-connected component is applied to label the connected area in the binary difference image. We remove the connected area which is too small. In our proposed, the pixel number of the connected area must be larger than 1000 pixels.
To obtain the boundary of the moving object, we denote the most left pixel of the connected area and the most right pixel of the connected area as the left boundary and the right boundary. The top pixel of the connected area and the bottom pixel of the connected area are the top boundary and the bottom boundary. The moving object boundary is shown in Fig. 4. We filter out the moving object whose width is too small because it could be not a car.

![Fig. 4: The white rectangle is the boundary of the moving object. The gray points are the connected area in the binary difference image.](image)

3.3. Update the background

The reference background image maintenance is a very important process. When the image is not including any moving object, we update the reference background image by a common background update rule in

$$f_b(x,y) = \alpha f_e(x,y) + (1-\alpha) f(x,y),$$

where the $\alpha$ is a update coefficient ($0 \leq \alpha \leq 1$) [12]. The $\alpha$ is 0.95 in our proposed method.

3.4. Estimation the rough plate size

Before the RTCLPD, we need the rough plate size of the moving object. The rough plate size, $P_w$ and $P_h$, and the parameter, $S_w$, for RTCLPD have to be estimated. We estimate the rough plate size by the ratio of the real car width to the real plate width. The ratios have invariable range. The ratio of the real plate width to the real car width is 1:5 to 1:6 in Taiwan. If the rough plate size is too small, it could be splitting the real plate. For avoiding that, this ratio is planned as 1:4. The ratio of the real plate width to the real plate height is 1:2 to 1:2.2 in Taiwan. We consider the angle of the image. This ratio is planed as 1:2.5 and the ratio of the distance of the grid point to the rough plate height is 1:3. Therefore, the suitable rough plate size and the parameter for detection are estimated by

$$P_w = \frac{1}{4} C_w,$$

$$P_h = \frac{1}{2.5} P_w,$$

$$S_w = \frac{1}{3} P_h,$$

where $C_w$ is the width of the moving object.

3.5. First derivate and smooth thresholding

After the rough plate size is estimated, the RTCLPD is applied in each moving object. The reliable binary edge information which is obtained by first derivate in the horizontal direction and smooth thresholding is the first work in the RTCLPD. We only obtain the binary edge information in the under-half of the moving object because the car license plate is located at the bottom of the car.

The simple edge information is obtained by first derivate in the horizontal direction, Eq. (6).

$$f(x,y) = f(x-1,y) - f(x+1,y),$$

where $f(x,y)$ is the edge information at $(x,y)$ and the coordinate $(x,y)$ is located at the under-half of the moving object.

After the first derivate in the horizontal direction, we use smooth thresholding to obtain the obvious edge information. There are two steps in the smooth thresholding. The steps are Eq. (7) and Eq. (8).

$$f'(x,y) = \begin{cases} 0, & \text{its 8-neighbor pixels } E_t \\ f(x,y), & \text{otherwise} \end{cases},$$

where $f'(x,y)$ is the result of first smooth thresholding step and $E_t$ is a predefined threshold value.

$$f''(x,y) = \begin{cases} 0, & f'(x,y) \leq E_t \\ 1, & f'(x,y) > E_t \end{cases},$$

where $f''(x,y)$ is the binary edge information at the coordinate $(x,y)$.

3.6. Rough region detection

We set the grid points in the binary edge information and every grid point, $(x_g, y_g)$, is distance $S_w$ to each other. The height of the grid point area is from the center of the moving object to the bottom of the moving object. The width of the grid point area is from $0.3C_w$ to $0.7C_w$. The grid point area is shown in Fig. 5.
We compute the number of pixels whose value is 1 in the edge information between \((x_g - \frac{1}{2} P_w, y_g)\) and \((x_g + \frac{1}{2} P_w, y_g)\). We denote the center point of the raw region as \((x_{gc}, y_{gc})\) which is grid point has the maximum number of pixels whose value is 1. The left-top point \((x_{cl}, y_{cl})\) and right-bottom point \((x_{cr}, y_{cr})\) of the raw region are denoted as

\[
(x_{cl}, y_{cl}) = (x_{gc} - \frac{1}{2} P_w, y_{gc} - \frac{1}{2} P_h),
\]

\[
(x_{cr}, y_{cr}) = (x_{gc} + \frac{1}{2} P_w, y_{gc} + \frac{1}{2} P_h).
\]

The mean position of pixels whose value is 1 in the raw region is computed by

\[
(\bar{x}, \bar{y}) = \left( \frac{1}{n} \sum x_i, \frac{1}{n} \sum y_i \right),
\]

where \((x_i, y_i)\) is the coordinate of pixels whose value is 1. \(n\) is the number of pixels whose value is 1 in the raw region. The center point of the rough region is \((\bar{x}, \bar{y})\). The left-top point \((x_{pl}, y_{pl})\) and right-bottom point \((x_{pr}, y_{pr})\) of the rough region are denoted as

\[
(x_{pl}, y_{pl}) = (\bar{x} - \frac{1}{2} P_w, \bar{y} - \frac{1}{2} P_h),
\]

\[
(x_{pr}, y_{pr}) = (\bar{x} + \frac{1}{2} P_w, \bar{y} + \frac{1}{2} P_h).
\]

Sometime, the maximum number of the binary edge information is not a car license plate. It could be the water tank or the lamp. We obtain two rough regions to reduce the error detection. When the first rough region is detected, we let the pixels whose location is between \(y_{pl}\) and \(y_{pr}\) in the edge information are 0. Then, perform the rough region detection again.

### 3.7. Accurate region detection

Two rough regions are detected. We have to obtain the accurate region because the rough region is larger than real plate region. The accurate regions are obtained by simple rules. To obtain the accurate width of the plate, we scan x-axis from the boundary of the rough region to the center of the rough region. When the number of pixels whose value is 1 at single vertical lines is larger than \(0.5 P_h\), stop scanning. For the accurate height, the scan direction is from the center of the rough region to the boundary of the rough region. When a single horizontal line is not including any pixel whose value is 1, stop scanning. The accurate regions are detected.

### 3.8. Real plate recognition

Three conditions are used to recognize suitable plate. The conditions are following:

a.) The width of the accurate region is not too small.

\[
PC_w > \frac{1}{2} P_w,
\]

where \(PC_w\) is the width of the accurate region.

b.) The accurate region width to height ration is correct.

\[
1.5 < \frac{PC_w}{PC_h} < 3.0,
\]

where \(PC_h\) is the height of the accurate region.

c.) There is enough number of the binary edge information in the accurate region.

\[
\frac{N}{A} > S,
\]

where \(N\) is the number of the pixels whose value is 1 in the accurate region, \(A\) is the area of the accurate region and \(S\) is a predefined threshold.

The suitable plate is detected by the conditions. There are three possible results. First result, there is no suitable plate which is detected. We believe there is no real plate in this moving object. Second result, only one suitable plate is detected. This suitable plate is denoted as the real plate in this moving object. The last possible result, both accurate regions are suitable plates. We denote the suitable plate whose location is near bottom of the moving object as the real plate.

A real plate in a moving object is detected. We repeat subsection 3.4 to subsection 3.8 to detect the real plate in each moving object.
4. EXPERIMENTAL RESULTS

The experimental images are captured by the DV camera which is mounted on the footbridge. The image is 640 by 480 pixels. Two samples are captured. The sample 1 is captured at pm 3:30 and the sample 2 is captured at pm 12:30. The cars in sample 1 are larger than sample 2 and the images in sample 2 are lighter than sample 1. The images of samples are shown in Fig. 6.

We classify the images into group 1 and group 2. The images of group 1 are including the full car license plate and the images of group 2 are not. We have 5944 images in group 1 and 18777 images in group 2 and the number of cars is 124. The example images in group 1 and group 2 are shown in Fig. 6 and Fig. 7.

The system is built by C++ and process in 3.2GHz and 1GB RAM. The executable time for a frame is 0.03 to 0.06 seconds.

![Fig. 6: The images of group 1](image1)
![Fig. 7: The images of group 2](image2)

There are 115 cars which are detected in our proposed. The car detection ratio is 115/124 = 92.74%. The number of the images which are detected in group 1 is 5346. The ratio of the successful detection is 5346/5944 = 89.94%. The number of the images which are detected in group 2 is 291. The ratio of the error detection is 291/18777 = 1.55%. The results of our proposed are shown in Table 1.

<table>
<thead>
<tr>
<th></th>
<th>Sample 1</th>
<th>Sample 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of cars</td>
<td>44</td>
<td>80</td>
</tr>
<tr>
<td>Number of detected</td>
<td>42</td>
<td>73</td>
</tr>
<tr>
<td>Ratio of successful</td>
<td>95.45%</td>
<td>91.25%</td>
</tr>
<tr>
<td>Number of group 1</td>
<td>1755</td>
<td>4189</td>
</tr>
<tr>
<td>Number of detected</td>
<td>1633</td>
<td>3713</td>
</tr>
<tr>
<td>Ratio of successful</td>
<td>93.05%</td>
<td>88.64%</td>
</tr>
<tr>
<td>Number of group 2</td>
<td>13008</td>
<td>5769</td>
</tr>
<tr>
<td>Number of detected</td>
<td>57</td>
<td>234</td>
</tr>
<tr>
<td>Ratio of error detected</td>
<td>0.04%</td>
<td>4.06%</td>
</tr>
</tbody>
</table>

There are 216 images which are including two car license plates in our samples. Both the car license plates which are detected in an image are 131. The ratio of multi-plates successful detection is 131/216 = 60.65%. There are 85 images which are not all detected. There are 79 images which are one car license plate to be detected in 85 images. The detected ratio of one car license plate is 79/85 = 92.94% and the losing ratio is 6/216 = 2.78%. The examples of multi-plates are shown in Fig. 8 and the detection results of multi-plates are shown in Table 2.

![Fig. 8: The examples of the multi-plates](image3)
Table 2: The detected results of multi-plates.

<table>
<thead>
<tr>
<th></th>
<th>Both plates</th>
<th>One plate</th>
<th>Losing plate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of images</td>
<td>216</td>
<td>85</td>
<td>216</td>
</tr>
<tr>
<td>Number of detected</td>
<td>131</td>
<td>79</td>
<td>6</td>
</tr>
<tr>
<td>Ratio of success</td>
<td>60.65%</td>
<td>92.94%</td>
<td>2.78%</td>
</tr>
</tbody>
</table>

5. CONCLUSION

We used a simple moving object detection method to improve RTCLPD method for detecting multi-plates in an image. A simple condition is used to filter out the moving object which is not a car. If the moving object is a car, the rough plate size of the moving object is estimated for RTCLPD scheme. RTCLPD method is applied in each moving object and we detect the plate in the partial area of the moving object to reduce the computational time. According to the results, we detect the car license plate accurately in the real time system and there are more car license plates can be detected in an image.

REFERENCES