Non-motor vehicle illegal behavior discrimination and license plate detection based on real-time video

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Abstract. In recent years, automatic detection technology of motor vehicles has developed rapidly. However, due to some interference problems, there is little research on the automatic detection technology of non-motor vehicle. This paper proposes a method which based on the experience and results of actual projects for discriminating non-motor vehicles in real-time video, detecting and recognizing license plates. The algorithm and steps will be described in detail. The image difference method and fractional differential method are combined to extract the contours of dynamic non-motor vehicles in the video, and the methods are used to filter the contours of non-motor vehicles using skin color filter detection and geometric feature discrimination to assist the training of cascade neural networks. Non-motor vehicle license plate image clustering is detected in the extracted contour by clustering the background color of the license plate and determining the ratio of the rectangle surrounding the license plate. The boundary expansion method is used in combination with the Faster R-CNN (Faster-Convolutional Neural Networks) to train the model, and then BP (Back propagation) neural network is used to identify characters in the target area. And a trajectory tracking method is proposed to automatically determine whether non-motorized vehicles have violations.

1. Introduction

With the development of China's intelligent transportation field, good achievements have been made in many aspects, such as the intelligent identification of signal lights [2]. But the continuous improvement of technologies such as automatic detection of vehicle lanes and license plate recognition has greatly reduced the difficulty of relevant departments. However, unlike motor vehicles, non-motor vehicle models are diverse, vehicles and license plates are easily occluded, motion blur and high scene complexity make the detection and recognition of non-motor vehicle license plates much larger than that of motor vehicles. Moreover, the current research on non-motor vehicle violations is relatively less than that of motor vehicles. In order to solve this phenomenon, this article conducts a combination of actual projects such as tracking of non-motor vehicles, non-motor vehicle detection, and non-motor vehicle license plate detection and identification research.

According to the actual problems, this paper introduces self-learning technologies such as BP neural network, convolutional neural network, Faster R-CNN network for key technologies such as non-motor vehicle behavior discrimination, non-motor vehicle license plate detection, and license plate detection and recognition. The proposed extraction detection method, non-motor vehicle detection method, license plate detection method, non-motor vehicle license plate recognition method and trajectory extraction method will greatly improve the detection accuracy and efficiency.
2. Design and Implementation

This article proposes a more practical and effective method to detect non-motor vehicles based on the problems found in practice and the actual situation in production practice. That is, based on the traditional non-motor vehicle detection based on traditional moving targets, some non-motor vehicles are introduced. As a decision mechanism, screening non-motor vehicle contours can not only avoid the phenomenon of inaccurate detection when the neural network has not had enough iterations in the early stage, but also can use these images as the input of the neural network to iterate and improve. Performance of neural networks.

2.1. Non-motor vehicle detection

The two-frame difference method is used for differential image processing, and a combination of fractional differential and Canny-type edge detection [3] is used for preprocessing. Use the ellipse skin color detection model to filter the interference factors and keep only the non-motor vehicles and vehicles or pedestrians in the target. In order to reduce the interference of the shadows of night-moving objects that are easy to move, after skin color detection, the image is binarized by "emphasizing" the skin color and the threshold is used to determine whether the contour is the target detection object or interference. A large number of similar features are extracted and the contour image is subjected to secondary screening. Morphological processing is used to remove adhesion to improve accuracy. The extraction effect is shown in Figure 1.

2.2. Non-motor vehicle license plate detection and recognition

Non-motor vehicle license plates are rectangular, divided into three colors of white, yellow, and green. The aspect ratio and area are not the same. The author has carried out many experiments based on the sample license plates stored by the traffic management department, and according to the length of each color Based on the data of width ratio and sample area, a method for judging the length-width ratio and shape of non-motor vehicle license plates is obtained. The implementation flowchart is as follows:
2.2.1. Non-motor vehicle license plate detection

According to the non-motor vehicle license plate detection model, some key steps in the algorithm are analyzed in detail. The specific implementation steps of the algorithm are discussed below:

1. Extract images of non-motorized vehicle regions in video frames. Convert RGB color space to $Y’CbDr$ color space and perform histogram equalization on the three components of the conversion result. Calculate the total edge intensity. Perform improved Canny Edge detection on images;

2. At this time, the candidate contour area $area_i$ ($1 \leq i \leq m$) is obtained (i and m: number and total number of candidate contours), and the contour area coefficient is set to $\varphi$. Let the candidate rectangular outline have a length $W$ and a width $H$;

White and green license plates: Let the comparison area of the candidate contour $Area$ be $\frac{64}{12}$, the area $L$ of the candidate contour is $W \times H$, the rectangular coefficient of the candidate contour is $r = \frac{W}{H}$,

\[
\begin{align*}
\text{Min}_{area_i} &= 25 \times Area \times 25 \\
\text{Max}_{area_i} &= 195 \times Area \times 195 \\
\bar{r}_{\text{max}} &= Area + 2 \times Area \times \varphi \\
\bar{r}_{\text{min}} &= Area - 2 \times Area \times \varphi 
\end{align*}
\]  (a)

The criterion can be obtained, if $r < 1$, then $\frac{1}{r}$, then: a) $L < \text{Min}_{area_i}$; b) $L > \text{Max}_{area_i}$; c) $r < \bar{r}_{\text{min}}$; d) $r > \bar{r}_{\text{max}}$, when the four conditions are greater than or equal to one, it is determined as the contour of the candidate region, otherwise the contour is discarded (Same for yellow license plate);

3. Suppose that all the pixels in the candidate contours and the edges are the sample set $D = \{x_1, x_2, x_3 \ldots x_m\}$ (m: total number of pixels), and randomly select n in D as the initial mean of the samples. The vector $\{u_1, u_2, u_3 \ldots u_n\}$, Calculate the distance from the pixels in D to the mean vector $u_1, u_2, u_3 \ldots u_n$, classify them in order $l_1, l_2, l_3 \ldots l_n$ as the central class cluster after classification;

4. For the central class clusters $l_1, l_2, l_3 \ldots l_n$, continue to find new central class clusters $l'_1$, $l'_2$, $l'_3 \ldots l'_n$.
\( l_2', l_3', \ldots, l_j \), if \( j \neq n \), update, otherwise continue iterating until \( j = n \), and repeat steps (3) and (4), if \( j = 2 \) and if the number of sample points in the central clusters of the two are not equal, leave them as candidate license plate contours and perform step (5), otherwise discard them;

(5) For candidate rectangular contours that meet the requirements, select the central cluster with a large number of sample points as the background color, and convert these sample points into R, G, and B components according to the formula, and determine the bottom of the area surrounded by the contour according to the RGB color space model. Whether the color is one of yellow, white and green, if yes, leave the candidate rectangular outline; if not, discard it;

(6) Color-binarize the area surrounded by each contour, and perform first-close operation and then-open operation on each contour area after the color binarization;

(7) Count the number of candidate rectangular contours as \( \theta \), and count the white pixels (including the boundary) in their respective areas and set it to \( x \). Set a non-zero interval to \( (m, n) \), The discrimination condition is set to \( P = \frac{x}{W \times H} \) (W and H are the length and width of the image respectively);

\[
\begin{align*}
\theta = 1 & \text{ and } P \in (m, n) \quad \text{Determine the candidate area as a license plate} \\
\theta < 1 & \text{ or } \theta > 1, \text{ and } P \in (m, n) \quad \text{Go to step (9)} \\
\text{else} & \quad \text{No motor vehicle license plate in the determination area}
\end{align*}
\]

(8) Perform tilt adjustment on the final license plate obtained, extract the license plate after adjustment \([5]\), and save the sample data.

2.2.2. Non-motor vehicle license plate detection and recognition

The following is the license plate character recognition based on the license plate detection results. The specific steps and algorithms are:

(1) Binarize the license plate image in the obtained sample data, calculate the image histogram, and the average pixel value of the background and character is \( N_1 \) and \( N_2 (N_1 > N_2) \). Identify the numbers in the original image of the non-motor vehicle and obtain the digital area;

(2) First break digit discrimination: If the recognized license plate is a white the number of digits is greater than 6 digits, then discard; If the recognized license plate is a yellow license plate and the number of digits is greater than 7 digits, then discarded; Judgment: If the white (yellow) license plate is recognized and the number of digits is equal to 6 (7) digits, keep it and go to 2.2.2-(8); Digit discrimination: If the number of digits on the white (yellow) plate is less than 6 (7) digits;

(3) For the license plate with missing median for the third time, first perform histogram equalization, grayscale, edge detection, and morphological processing, and search for the missing number from the leftmost side of the string. If \( \sigma \) satisfies

\[
|\sigma - N_2| < |\sigma - N_1|
\]

(c) the number of pixels is more than 5, then the pixel is considered to be above or next to the numeric character. If the number of pixels in the column where the pixel is less than 200, the number of pixels is more than 10, it is judged that the pixel has fallen;

(4) Take this pixel as the center point, and search left and right respectively, until pixel value less than 200 on the left and the conditions described in (2) are not met, the two pixels are determined to be the numeric character. Boundary pixel, set the distance between each pixel point between the two pixels to 1, calculate the distance between the two pixels, and set the maximum width of the character to \( d_j \);

(5) Iteratively search according to the methods of (4) and (5) until each numeric character gets their maximum width \( d_{x_i} \) (i: number of digits of numeric characters), and find the average value \( \bar{d}_{x_i} \);

(6) Set an empirical value as \( \theta \) and a threshold value as \( T \). At this time, start from the leftmost side of the first numeric character and the rightmost side of the last character obtained from the calculation of the number of digits of the third judgment, according to (4), (5 ) and (6), if the maximum width of the obtained character satisfies \( |d_{x_i} - \theta| < T \), it is judged as another number , boundary is extended;

(7) Continue to search by the left of the leftmost first digit and sum the area mark of the numeric character area, denoted as \( \sum x_j \). If the searched pixel value satisfies the formula (c), continue to follow the horizontal and vertical directions. (4) Perform a search. If the number of pixels satisfying the formula...
is less than 3, mark and sum these pixels according to the area search method and record it as \( \sum x_2 \). If \( \sum x_2 < \frac{1}{5} \sum x_1 \), judge the area is the separation point between Chinese characters and numeric characters;

(8) Calculate the target area ratio, boundary angle and other related parameters in the original license plate image and used as a sample image of the input Faster R-CNN network to construct a Faster R-CNN network, and then use the constructed Faster R-CNN network detects target regions of non-motor vehicle original license plate images. Using BP neural network to recognize the character and number of the license plate in the target area of the original license plate image of the non-motor vehicle.

Figure 3. Non-motor vehicle license plate test results

2.3. Non-motor vehicle trajectory extraction
Select the adaptive mean shift method [5], use the color information in the video image as the extracted feature, and then perform mean shift on each frame of the input image, and then use the processed video frame as the initial value for the next processing and iterate repeatedly for tracking processing.

- First divide the entire zebra crossing area into three areas (area1, area2 and area3);
- In the red-light state, for area 1: if there is a non-motor vehicle, the non-motor vehicle is taken as the target, the frame is extracted as \( Q \). The detection frame for area2 is \( Q_1 \), and the detection frame for area3 is \( R_j \) (i, j: the total number of detection frames in area2 and area3). If a non-motor vehicle is found in area2, the frame is extracted and set to \( Q_m \) (1 ≤ m ≤ j). Similarly, if found in the target area2, the frame is extracted and set to \( R_n \) (1 ≤ n ≤ j). If at least one of \( Q_m \) and \( R_n \) exists, proceed to the next step, else, discard and return;
- According to the trajectory of the non-motor vehicle detected by the adaptive mean drift, it is determined whether the non-motor vehicles in \( Q_m \) and \( P \) or \( R_n \) and \( P \) or \( Q_m \) and \( R_n \) and \( P \) are the same vehicle. If yes, continue to the next step, otherwise, discard;
- Let the trajectory of the non-motor vehicle be \( T \), then set the position of the point target \( k \) on the frame \( R_n \) or \( Q_m \) to \((c_x, c_y)\), and set the position of the point target \( k-1 \) on the P frame to \((c_x - 1, c_y - 1)\), calculate the distance between \( k \) and \( k-1 \) as \( D \), and set the value of \( D \) between \([a, b]\);
- Let the coordinates of the center of gravity on the P frame be \( P(x, y) \) and the coordinates of the center of gravity on the \( R_n \) or \( Q_m \) frame be \( R_n(x, y) \) or \( Q_m(x, y) \), and calculate \( P(x, y) \) and \( R_n(x, y) \) or \( Q_m(x, y) \), and calculate their distance \( d \), until \( d \in [a, b] \) is satisfied, using the center of gravity point on the P frame as Horizontal plane, find the angle \( A \) between two points;
- Found the two points of gravity on the P frame, and connect the longest trajectory \( T \). Compared and corrected \( T \) with the extracted trajectory set to \( T' \). If it’s length and angle of \( T' \) both reach the preset thresholds, determined that the non-motor vehicle has a red-light running behavior.
Figure 4. Illegal vehicle tracking display

3. Conclusion
The correct detection of non-motor vehicles, and the correctness of non-motor vehicle license plate detection and recognition play a decisive factor in determining the success of later non-motor vehicles' red-light crossing behavior. The method proposed in the article is based on the experience of the actual project, but in order to improve the detection efficiency, some details need to be improved and perfected.

References
[1] Szeliski,R.(2011)Computer Vision: Algorithms and Applications. Springer-Verlag London, London.
[2] Arinaldi, A., Pradana J.A., Gurusinga A.A. (2018) Detection and classification of vehicles for traffic video analytics. Procedia Computer Science, Vol.144: 259-268.
[3] Yang, A.L., Jiang, WW., Chen, L. (2017) An Adaptive Edge Detection Algorithm Based on Improved Canny. Advanced Computational Methods in Life System Modeling and Simulation, Vol.761: 566-575.
[4] Yang, D., Zhou, H., Tang, L., Chen, S., Liu, S. (2018) A License Plate Tilt Correction Algorithm Based on the Character Median Line Algorithm de correction d'inclinaison de plaque d'immatriculation basé sur la ligne médiane du caractère (Article). Canadian Journal of Electrical and Computer Engineering, Vol.41: 145-150.
[5] Dhassi, Y., Aarab, A. (2018) Visual Tracking Based on Adaptive Mean Shift Multiple Appearance Models (Article). Pattern Recognition and Image Analysis, Vol.28: 439-449.