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Lane Detection Based on Machine Learning Algorithm

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Abstract

In order to improve accuracy and robustness of the lane detection in complex conditions, such as the shadows and illumination changing, a novel detection algorithm was proposed based on machine learning. After pretreatment, a set of haar-like filters were used to calculate the eigenvalue in the gray image f(x,y) and edge e(x,y). Then these features were trained by using improved boosting algorithm and the final class function g(x) was obtained, which was used to judge whether the point x belonging to the lane or not. To avoid the over fitting in traditional boosting, Fisher discriminant analysis was used to initialize the weights of samples. After testing by many road in all conditions, it showed that this algorithm had good robustness and real-time to recognize the lane in all challenging conditions.

Keywords: *lane detection, machine learning, haar-like, improved boosting algorithm*

1. Introduction

Lane detection becomes a hot issue in the filed of intelligent transportation, and the correct identification of lane is the basis of the lane departure warning systems and some other driver driving assistant systems. At present, many algorithms for this problem have proposed by researchers [1], such as the support vector machine [2-4], neural network [5], Hough transform [6], template matching and so on. However, these methods are still difficult to apply in all situations. The robustness and accuracy of lane recognition remain to be further improved for the complex road environment, especially the existence of a large number of shadows and illumination changes.

Toward this end, a novel lane detection algorithm based on machine learning is proposed in this paper to solve the hard detection in complex conditions. In this algorithm, haar-like features are used to extract sharp features and improved boosting algorithm is used to train these features. The improved boosting algorithm is different from the traditional algorithm in initialization. Before initialization in boosting, the kernel Fisher discriminant analysis is used to show this sample's relative importance and initialize the sample weight according to the relative importance. After done the above work, the final classification function g(x) will be obtained to classify the point x.

This article is structured as follows: section 1 presents the theory and method of this algorithm including pretreatment, haar-like, and improved boosting. After experiment by 200 images, the result and comparation with other methods are presented in section 2.

2. Research Method

2.1. Pretreatment

The preprocessing of the image is intended to accelerate the image processing, filters the noise and interference in the image, and improves the recognition accuracy. For the images captured by the camera, dividing the region of interest (ROI), graying, and median filtering are sequentially used to get the pretreated image f(x,y).

Dividing the region of interest is a common preprocessing method which marks the region of interest according to the position of object in the image. For the road image, lane markings always locate in the lower part of the image. Thus set the upper 5/12 as ignored region and the lower 7/12 as the region of interest. Moreover, according to the symmetry of the lane, the left lane and right lane are located in the left side and the right side of the vehicle. In

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order to speed this algorithm, graying and median filter are used in the lower left 7/24 and the lower right 7/24 respectively. The result f(x,y) is shown in Figure 1.

Original image Graying Median filter and ROI

Figure 1. The Pretreatment of Road Image

2.2. Feature Extraction

The canny operator is used in the image f(x,y) and the edge extracted image e(x,y) is got. Supposed that the x_i is a point in f(x,y), and $S(x_i)$ is a 3*3 neighbor region of x_i. $S(x_i)$ is denoted as $S_f(x_i)$ in the f(x,y), and $S(x_i)$ is denoted as $S_e(x_i)$ in the e(x,y). The final strong classifier is obtained by two steps: 1) Compute eigenvalues of haar-like in $S_e(x_i)$ and $S_f(x_i)$ respectively. 2) Send the eigenvalues as the input of the following improved boosting algorithm. Then according to the result of the final strong classifier, we can know whether the point x_i belong to set O or set O', where the set O is points collection of lane and the set O' is the points collection of noise. The process of this algorithm is shown in Figure 2.

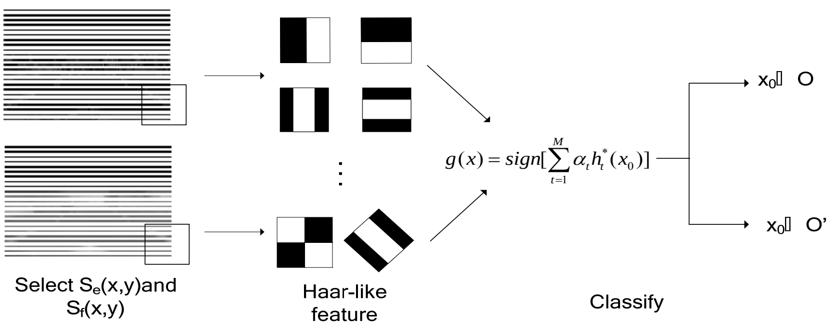

Figure 2. The Process of this Algorithm

Haar-like feature was proposed by Viola and Jones for face recognition, which has become one of the most commonly used feature in classification problems. Its simple computation and short operation time make it better than other features in all kinds of classification, and when deals with the integral image, the advantages are more obvious.

At present, the commonly used features in haar-like are following in Figure 3:

Features of Figure 3(a), (c) and (d) are selected because of the strong gradient of the lane. And the features of Figure 3(e), (g), (h), (i) and (j) are selected because of the linear structure of the lane. So for the left lane region, features 3(a), (d), (e), (h) and (j) should be used to detect the left lane, and for the right, features 3(a), (c), (e), (g), and (i) should be used. The characteristic value of the haar-like feature is defined as the subtraction between the sum of pixels in the white rectangular and the sum of pixels in the black rectangular. But in this paper, the characteristic value is redefined. The value is only equals to sum of all the pixels in the white rectangular in order to improving the real-time of this algorithm.

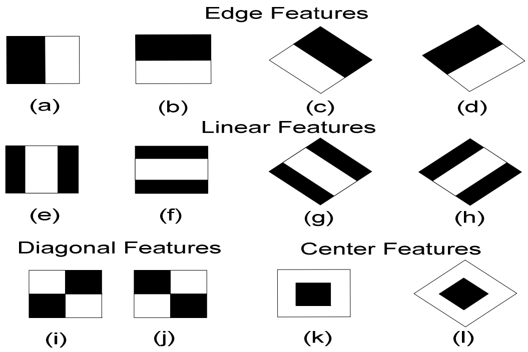

Figure 3. The Commonly used Haar-like Features

In the processing of computation, to calculate the haar-like characteristic value, addition operation is required to repeat many times. In order to avoid repeated computation and improve processing speed, the integral image is used in this paper, which is shown in Figure 4. In the integral image II(x,y), the value of an arbitrary point is equal to the sum of all pixels in the upper left corner of the original image I(x’,y’), which is calcualted as the following equation:

$$II(x,y) = \sum_{x' \le x, y' \le y} I(x',y') \tag{1}$$

When the integral image is rotated 45 degrees, an arbitrary point value is corresponding to the following formula:

$$II(x,y) = \sum_{x' \le x, x' \le x - |y' - y|} I(x',y') \tag{2}$$

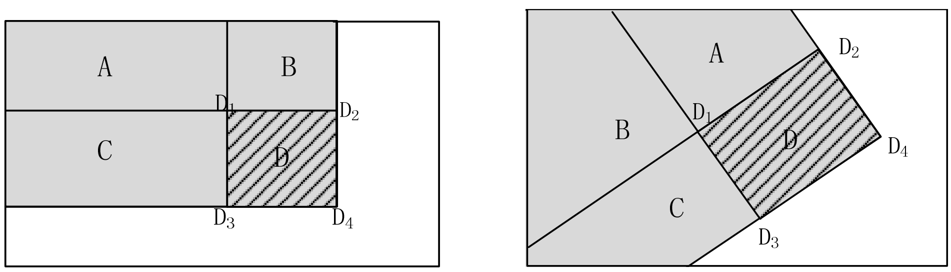

Figure 4. Integral Images

For the two integral images in Figure 4, the sum of all pixels in the region D can be got by using the following equation:

$$sum(D) = D_4 + D_1 - D_2 - D_3 \tag{3}$$

Where D_1, D_2, D_3, D_4 are the four corners of region D, and D_1=sum(A), D_2= sum(A+B), D_3= sum(A+C), D_4= sum(A+B+C+D). So by using these equations, if we know four coordinates of corners, the characteristic value can be easily calculated.

2.3. Improved Boosting Algorithm

Boosting algorithm uses a set of weighted weak learners to combine a strong classifier and it is always used to classify two aspects. For the lane recognition, an improved boosting algorithm is put forward to classify a point whether it belong to lane.

In the traditional boosting algorithm, all samples have same weight in the initialization. After a cycle, the weights of wrong classified samples will be increased, so in the next iteration, these misclassified samples should be paid more attention. But for outliers, the weights become greater and greater with the increase of iterations. Finally, the excessive focusing on some mislabel or indistinguishable samples will affect the performance of the classifier. This is called the over fitting.

Therefore, in order to improve the above shortcomings, an improved boosting algorithm is proposed in this paper. In practice, some samples are more representative than some other samples. Before using the boosting algorithm, according to the prior knowledge, the weight of some more representative sample is set bigger than others in the initialization. In this situation, the weight growth rates of indistinguishable or mislabel samples will slow down, due to the lower weights at the beginning, so it can effectively avoid over learning.

Supposed (x_i, y_i) $i\in\{1,2,\ldots,N\}$ represents the i-th trained sample data, where $x_i \in R^N$ is the i-th trained sample and $y_i\in\{1,-1\}$ is the label of x_i. In order to get the importance of a feature point, the fisher discriminant analysis is used. First, define the projection direction α, and project x_i to a new feature space z_i, where the value of α can be got by the following equation:

$$J(\alpha)=\frac{\alpha^T B\alpha}{\alpha^T W\alpha} \tag{4}$$

Where, B and W represent the between class scatter and within class scatter. When J(α) is maximum, the value of α is the wanted projection direction.

Then z_i is got, which is the projection of x_i along the α:

$$z_i=\alpha x_i \tag{5}$$

And calculate a parameter β_i:

$$\beta_i=\frac{|z_i-\overline{z}_i|}{\sum_{\forall y_k=y_i}|z_i-\overline{z}_i|} \tag{6}$$

Where, $\overline{z}_i$ ($i\in\{-1, 1\}$) represents the mean of the set of all z_i, and β_i is the distance between z_i and its class mean $\overline{z}_i$. If the weight is w_i, the new weight W_i is:

$$W_i=w_i*\exp(\tau*\beta_i) \tag{7}$$

Where, τ is a coefficient to adjust the importance of weights and the accuracy of this method. For example, when τ is smaller, it means the fisher discriminant analysis less important. When τ close to 0, W_i is almost equal to w_i, which means that all samples' weights have same weight and this Fisher discriminant analysis is not used. So adjusting τ can adjust the importance of the Fisher discriminant analysis.

The improved boosting algorithm we proposed is shown below:

Sample set is {x_i, y_i} i={1,2,…, N}, where $x_i\in R^N$ is i-th sample data, $y_i\in\{-1,1\}$ is label of i-th sample. H={h_1, h_2,…, h_M} is a set of all weak classifiers.

Initialize the weight of samples by using this equation:

$$W_1(i)=\frac{1}{N}\exp(-\tau\beta_i),\forall i=1,2,\cdots N \tag{8}$$

For t=1,2,…,T

1) Calculate the classification error of classifier h_t:

$$E_t = \sum_{i=1}^{N} W_t(i) I[y_i \neq h_t(x_i)] \quad (9)$$

Where $h_t(x_i) \in H$, which is a weak classifier, and I is the indicator function. When E_t is minimum, the ht is called ht* in the above equation.

2) Setup α_t:

$$\alpha_t = 0.5 \ln \frac{1 - E_t}{E_t} \quad (10)$$

3) Update weight:

$$W_{t+1}(i) = \frac{W_t(i) \exp(-\alpha_t y_i h_t^*(x_i))}{M_t} \quad (11)$$

In the above equation, M_t is a normalization factor.
The final class function:

$$g(x) = sign(\sum_{t=1}^{M} \alpha_t h_t^*(x_i)) \quad (12)$$

$g(x) \in \{1,-1\}$ represents the point x belonging to O or O'. In the image f(x, y), delete the point whose class function g(x) is equal to -1, and reserve the point whose class function g(x) is equal to 1. Then, for the remaining points, the least square fitting is used to fit the lanes.

3. Results and Analysis

In order demonstrate the robustness and accuracy of this method; we captured 200 images to test in all conditions, such as shadows, illumination changes, and so on. Then divide these 200 road images into two groups. One group is used for training, and the other is used for test, and each the image resolution is 240*320.

To verify the robustness of the algorithm, we make experiment in the test group. Supposed that the real point of lane is marked as P and the point which got by our algorithm is marked as P*, the distance between the P and P* can be calculated. The results shown that the P* is in a R×R neighborhood around the P, thus the ROC curve (receiver operating characteristic curve) in the test group can be drawn by statistics, which is shown in Figure 5.

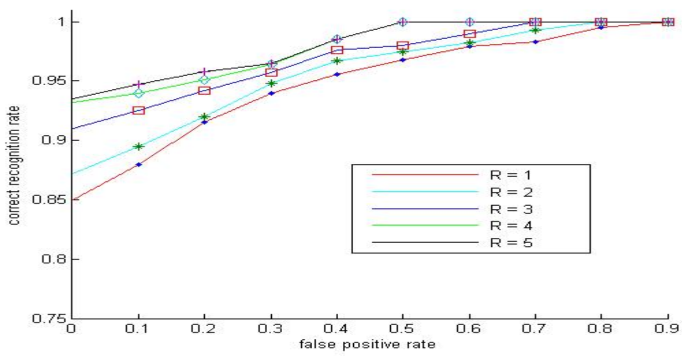

Figure 5. The ROC Curve

In the above figure, the horizontal axis is the false positive rate, and vertical axis is correct recognition rate. From the curves, we can find that the accuracy is higher when the R is bigger. When false positive rate is equal to 0 and R=1(P* is P), the accuracy of this algorithm is about 85%. Because the lane recognition is mainly used for vehicle navigation, lane departure warning and driver assistant systems, the approximate location of lanes is only needed in these systems to provide services instead of exact location, so R≠1 is within acceptable limits. When R=4 and 5, the distance between the P* and P is far and will affect the least squares fitting. When R=3, the distance between the P* and P is optimum, thus in this paper, the accuracy means P* is in a 3×3 neighborhood around of P.

To verify the performance of this algorithm, three methods are chosen in this paper. The first one is using haar-like feature and traditional boosting algorithm to design a classifier, the second one is using SVM (Support Vector Machine), and the third one is our algorithm, which using the haar-like feature and improved boosting algorithm to design a classifier. To compare the performance of three methods, the same train and test samples are used in a same condition. The recognition results are shown in Figure 6.

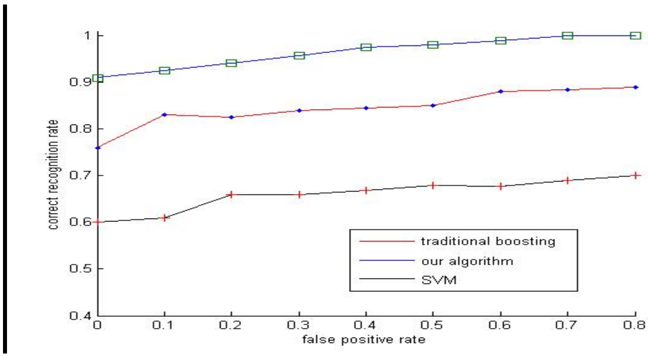

Figure 6. The Comparation of Three Algorithms

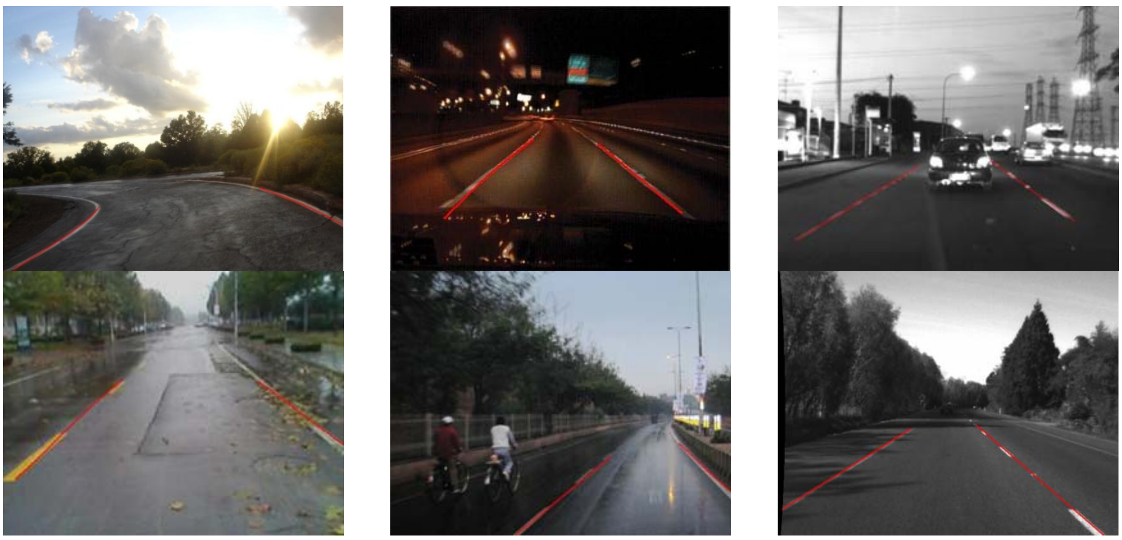

Figure 7. The Results of Complex Conditions

From the above figure, we can see that the two methods using haar-like feature to extract the lane features are better than the SVM. The reason is that the haar-like feature is not only considers the linear feature of the lane, but also considers the environment of points. Judging the point mixed with road information can greatly improve the accuracy of the classifier.

In addition, comparing the upper two curves, we can find that our algorithm is obviously superior to the traditional boosting algorithm under various road conditions. It also proves that our algorithm combined with prior knowledge in the initialization is better than the traditional boosting algorithm.

To determine the reliability and applicability, our algorithm has been tested in many road conditions. The red line in Figure 7 is the detection results in some challenging conditions by using this algorithm. From these pictures we can see that no matter in rainy, worn, night, and shadow conditions, this algorithm can correctly and robustly recognize the straight or curve lane perfectly.

4. Conclusion

In order to improve the robustness and accuracy of lane detection algorithm in complex conditions, such as shadows and illumination changing. A lane detection algorithm is proposed based on machine learning. Haar-like feature extraction and boosting are combined to design a classifier. First, extract the haar-like features in an lane image, these features combined with environmental information can effectively improve the lane recognition accuracy. Then, the improved boosting algorithm is used to avoid the over fitting of traditional algorithm, so that the improved algorithm has better anti-noise performance. Verified by a large amount of experiments, the results show that our algorithm can detect the straight or curve lane correctly in kinds of complex condition.

References

[1] JC McCall, MM Trivedi. Video-based lane estimation and tracking for driver assistance: survey, system and evaluation. *IEEE Transactions on Intelligent Transportation Systems*. 2006; 7(1): 20-37.

[2] HM Mandalia, DD Dalvucci. *Using Support Vector Machines for Lane-Change Detection*. In Proceedings of the Human Factors and Ergonomics Society 49th Annual Meeting. Santa Monica. 2005; 1965–1969.

[3] N Mechat, N Saadia. *Lane detection and tracking by monocular vision system in road vehicle*. Image and Signal Processing (CISP). 5th International Congress on. Chongqing. 2012: 1276-1282.

[4] Z Kim. Robust Lane Detection and Tracking in Challenging Scenarios. *IEEE Transactions on Intelligent Transportation Systems*. 2008; 9(1): 16–26.

[5] S Baluja. Evolution of an artificial neural network based autonomous land vehicle controller. *IEEE Systems, Man, and Cybernetics Society*.1996; 26(3): 450-463.

[6] He Mao, Mei Xie. *Lane detection based on Hough transform and endpoints classification*, Wavelet Active Media Technology and Information Processing (ICWAMTIP). International Conference on. Chengdu. 2012; 125-127.