An Unstructured Road Detection Method with Multi-environmental Adaptability

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Abstract — The environments of unstructured roads are complex and have more interference factors, which cause many difficulties in detecting it. To solve this problem, this paper proposes a road detection algorithm based on the integration of adaptive threshold selection and anti-noise morphology edge detection. The detection algorithm first segments the road image using the threshold segmentation method based on minimum within-cluster variable exponent variance. Then, using anti-noise morphological edge detection algorithm, it filters the image and detects the road edge. Last, the road boundary is extracted by using Hough transform. The results of the experiments on unstructured road detection under three different scenarios indicate that the proposed algorithm can effectively identify unstructured road and has a better robustness under the influence of light and shadow, illumination changes, water stains and other adverse factors.

Keywords - unstructured road; multi-environmental adaptability; road image segmentation; edge detection; hough transform

I. INTRODUCTION

Road detection is the core and key technology of the research on the visual navigation of unmanned vehicle. Only measure road information precisely, can obtain position and direction of the vehicle relative to the road accurately in the process of driving [1].

Road is divided into structured road and unstructured road. Structured road has clear lane marks and road boundaries and its testing method has been relatively mature at present. Unstructured road is lack of clear lanes marking and its scene is complicated and easy to be influenced by many factors and difficult to detect. In view of the problem of the detection of unstructured road, the existing methods were mainly divided into three categories: the approach based on road model, the approach based on road feature and the approach based on neural network. The approach based on model is that realize the detection of unstructured road under the premise of assuming road model based on prior knowledge and its effectiveness is limited by the choice of the model to some extent. K. Wang et al. constructed uncertain road deformable template using Bezier curve, and convert the road recognition problem to template parameter hypothesis testing problem. Research proposed a road detection method based on graph model. The authors divided the road image into sub-graph and calculated feature vectors. Then by setting the sampling window, extracted the road nodes and realized the road image segmentation. The approach based on feature includes color, gray, texture and other detection methods. Y. Z. Wang et al. presented a new method for detecting the vanishing point of unstructured road based on Haar texture. They designed real and imaginary Haar templates. By using integral image technique, realized the fast complex response of Haar texture and then using the orthogonal rectification and diversity voting methods, realized the vanishing point detection. According to the probability of the pixels belonging to the color model, some researchers carried out road segmentation and combined both segmentation and edge information. Then by using dynamic programming found an optimal concatenation of edge.. F. Bernuy et al. realized unstructured road detection by combining color histogram and random sampling. In order to improve the accuracy and robustness of the detection method of unstructured road, the method of multi-feature integration has become a hot research in recent years. A road detection approach based on color Gaussian mixture model and parabolic model improved the anti-interference ability in the process of unstructured road detection. Research using HSV image model as input variables of support vector machine classification algorithm realized the pixel classification for pavement and non-pavement.

Aim at unstructured roads with complex scenes, this paper proposed an unstructured road detection algorithm combined both threshold segmentation arithmetic based on the minimum within-cluster variable exponent variance and anti-noise morphological edge detection algorithm. By analyzing the principle of Otsu to obtain the optimal threshold, presented an adaptive modified Otsu method to segment the road image into the pavement and the non-pavement region. And then using anti-noise morphological edge detection algorithm detected the road edge. At last, the road boundary was extracted by using Hough transform.

II. ROAD SEGMENTATION BASED ON MINIMUM WITHIN-CLUSTER VARIABLE EXPONENT VARIANCE

A. Maximum Between-cluster Variance Method (Otsu)

In the year of 1979, Japanese famous scholar put forward Otsu method, which is image threshold segmentation arithmetic based on maximum between-cluster variance. According to grayscale, the method divides the
original image into background and objective and maximized between-cluster variance. This method is often applied to road detection.

Assuming that the grayscale of road image is $I$, the frequency of gray pixel $i$ is $p_i$, and the threshold $T$ divided the pixels less than $T$ as background and the pixels more than $T$ as objective.

Then the probability that each pixel is classified as background or objective is shown in equation (1),

$$
P_b(T) = \sum_{i=0}^{l-1} p_i, \quad P_o(T) = \sum_{i=l}^{2l-1} p_i$$

The gray average that pixels are assigned to the background region and the objective region respectively and the average gray of all pixels are shown in equation (2),

$$
\mu_b(T) = \frac{1}{P_b(T)} \sum_{i=0}^{l-1} i p_i,
\mu_o(T) = \frac{1}{P_o(T)} \sum_{i=l}^{2l-1} i p_i
$$

$$
\mu(T) = \sum_{i=0}^{2l-1} i p_i
$$

The gray variance that pixels are assigned to the background region and the objective region and the gray variance of all pixels are shown in equation (3),

$$
\sigma_b^2(T) = \frac{1}{P_b(T)} \sum_{i=0}^{l-1} (i - \mu_b(T))^2,
\sigma_o^2(T) = \frac{1}{P_o(T)} \sum_{i=l}^{2l-1} (i - \mu_o(T))^2,
\sigma^2(T) = \sum_{i=0}^{2l-1} (i - \mu)^2
$$

As shown in equation (4), the Otsu method generally chooses between-cluster variance as the criterion function of obtaining optimal threshold.

$$
C = \sigma_b^2(T) = P_b(T)(\mu_b(T) - \mu)^2 + P_o(T)(\mu_o(T) - \mu)^2
$$

Where, $C$ is criterion function and $\sigma_b^2(T)$ is between-cluster variance.

The optimal threshold $T_{opt}$ of Otsu method can be obtained by maximizing the between-cluster variance $\sigma_b^2(T)$. The judgment equation is as follows,

$$
T_{opt} = \text{Arg min}_{0 \leq T \leq 2l-1} \left( \sigma_b^2(T) \right)
$$

Gray variance of the image is equal to the sum of between-cluster variance and within-cluster variance. And the gray variance of image is constant, so the equation (6) is equivalent to equation (5),

$$
T_{opt} = \text{Arg min}_{0 \leq T \leq 2l-1} \left( \sigma_b^2(T) \right)
$$

Where, $\sigma_b^2(T)$ is within-cluster variance.

According to equation (5) and (6), we can see that minimizing within-cluster variance and maximizing between-cluster variance to obtain optimal threshold are equivalent. Therefore the equation (4) can be rewritten as follows,

$$
C = \sigma_b^2(T) = P_b(T)\sigma_b^2(T) + P_o(T)\sigma_o^2(T)
$$

The proposed algorithm has a better segmentation effect when the histogram of image has obvious doublet feature or the image has high signal-to-noise ratio. On the contrary, it is not ideal.

B. Improved Otsu Algorithm

In order to solve this problem, many improved algorithms are proposed. According to the probability difference between background region and objective region, Z. Houetal et al. presents a threshold method based on minimum class variance. The criterion function of this proposed method is shown in equation (8),

$$
C = \sigma_b^2(T) + \sigma_o^2(T)
$$

In this method, the optimal threshold is obtained by minimizing the criterion function of the equation (8).

However, when histogram has a single peak feature or has an obscure doublet feature, it is difficult to realize the effective segmentation of gray images.

Research put forward a threshold method based on minimum within-cluster absolute difference. The criterion function of this proposed algorithm is shown in equation (9),

$$
C = S_a(T) = P_b(T)d_b(T) + P_o(T)d_o(T)
$$

Where, $S_a(T)$ is total within-cluster absolute difference. $d_b(T)$ and $d_o(T)$ are within-cluster absolute difference of background region and objective region respectively, which can be calculated as follows,

$$
d_b(T) = \frac{1}{P_b(T)} \sum_{i=0}^{l-1} |i - \mu_b(T)|
d_o(T) = \frac{1}{P_o(T)} \sum_{i=l}^{2l-1} |i - \mu_o(T)|
$$

Similarly, the method obtained the optimal threshold by minimizing the total within-cluster absolute difference.

When the histogram of image is uniformly distributed and has more outliers, using minimum within-cluster absolute difference method can obtain better segmentation results. Whereas when the histogram of image has obvious doublet feature or a single peak feature, the segmentation effect is undesirability.

C. Threshold Segmentation Based on Minimum within-cluster Variable Exponent Variance

The three methods including Otsu method and the approaches proposed by Z. Houetal and Y. Q. Wu have better segmentation effects for some particular type of histogram. However, because of the complexity of the environments, the shape of histogram is varied in the actual process of unstructured road detection. In order to make the
algorithm have better environmental adaptability, by considering these three methods comprehensively, this paper puts forward a threshold segmentation based on minimum within-cluster variable exponent variance. The criterion function for selecting optimal threshold was shown in equation (11),

\[
C = \frac{1}{\left[P_o(T)\right]} \sum_{i=0}^{T} p_i \left(\left|\mu_i - \mu_o(T)\right|\right)^{E_1} + \frac{1}{\left[P_o(T)\right]} \sum_{i=T+1}^{m} p_i \left(\left|\mu_i - \mu_o(T)\right|\right)^{E_2}
\]

(11)

Where, \(E_1\) and \(E_2\) are variable exponent parameters.

When \(E_1=0\), \(E_2=2\), the equation (11) represents the criterion function of the Otsu method based on minimum within-cluster variance. The derivation process as follows,

\[
C = \frac{1}{\left[P_o(T)\right]} \sum_{i=0}^{T} p_i \left(\left|\mu_i - \mu_o(T)\right|\right)^{2} + \frac{1}{\left[P_o(T)\right]} \sum_{i=T+1}^{m} p_i \left(\left|\mu_i - \mu_o(T)\right|\right)^{2}
\]

\[
= \sum_{i=0}^{T} p_i \left(\left|\mu_i - \mu_o(T)\right|\right)^{2} + \sum_{i=T+1}^{m} p_i \left(\left|\mu_i - \mu_o(T)\right|\right)^{2}
\]

\[
= P_o(T) \frac{1}{P_o(T)} \sum_{i=0}^{T} p_i \left(\left|\mu_i - \mu_o(T)\right|\right)^{2} + P_o(T) \frac{1}{P_o(T)} \sum_{i=T+1}^{m} p_i \left(\left|\mu_i - \mu_o(T)\right|\right)^{2}
\]

\[
= P_o(T) \sigma_o^2(T) + P_o(T) \sigma_o^2(T)
\]

Similarly,

When \(E_1=1\), \(E_2=2\), the equation (11) represents Z. Hou et al. proposed criterion function based on minimum class variance.

When \(E_1=0\), \(E_2=1\), the equation (11) represents Y. Q. Wu presented criterion function based on minimum within-cluster absolute difference.

As we can see, this proposed criterion function is equivalent to the Otsu method and the methods presented by Z. Hou et al. and Y. Q. Wu when exponent parameters are taken for a specific value. From above, we can explain the rationality of the algorithm of this paper. This proposed algorithm can adaptively choose the exponent parameters according to the different shapes of the histogram. Using original Otsu method and the proposed method respectively, this paper carries out road segmentation of the unstructured road under different circumstances. The comparison experiment results are shown in Figures 1, 2, 3.
III. Filtering and Edge Detection

The road images are acquired by the camera mounted above the intelligent vehicle. Therefore, in the process of image acquisition, the clarity of the image is not particularly high, especially the noise is more serious because of the influence of pavement and other external interference factors. In recent years, the edge detection of noisy images based on morphological operations has become a hot research. In order to reduce noise, enhance edge details and reduce false edges, we proposed an edge detection algorithm based on anti noise morphology to realize edge extraction of road image.

3) As shown in the table I, structural element B are combined with four kinds of linear structures whose angles with horizontal direction are 0°, 45°, 90° and 135° and two scales respectively. And eight edge images are obtained according to the algorithms of the first two steps.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Direction</th>
<th>3x3</th>
<th>5x5</th>
</tr>
</thead>
<tbody>
<tr>
<td>0°</td>
<td>B1</td>
<td>B2</td>
<td></td>
</tr>
<tr>
<td>45°</td>
<td>B3</td>
<td>B4</td>
<td></td>
</tr>
<tr>
<td>90°</td>
<td>B5</td>
<td>B6</td>
<td></td>
</tr>
<tr>
<td>135°</td>
<td>B7</td>
<td>B8</td>
<td></td>
</tr>
</tbody>
</table>

4) Eight pairs of edge images are multiplied by their weight coefficient $w_j$ respectively, and then the final edge is obtained by adding, as shown in the equation (15),

$$ F = \sum_{j=1}^{8} w_j F_j $$  (15)

Weight coefficients can be calculated according to the following steps.

1) Calculate information entropy of eight edge images respectively, as shown in the equation (16),

$$ H_j = -\sum_{j=1}^{8} w_j \log w_j $$  (16)

2) Calculate weight coefficient, as shown in the equation (17),

$$ w_j = H_j \sum_{j=1}^{8} H_j $$  (17)

IV. Road Detection Based on Hough Transform

Although the shape of unstructured road is complex and the shape of its boundary is irregular, in most cases, we can still roughly approximate the road boundary in front of intelligent vehicle by a straight line. Therefore this paper used Hough transform to extract final road boundary.

Using polar coordinates equation, Hough transform was used to map the feature points of image into a sine curve of the parameter space. The mapping relationship is shown in the formula (18):

$$ \rho = x \cos \theta + y \sin \theta $$  (18)

Where, $\rho$ is the distance of origin to the straight line, $\theta$ is the angle between horizontal axis and normal of the straight line. As shown in Figure 4.

Figure 4. Mapping relationship

The implementation steps of edge detection algorithm based on anti noise morphological are as follows.

1) Using Structural element B filter input image and extract the edge of image, as shown in equation (13),

$$ Y_i = f(x, y) BB - f(x, y) B $$

$$ Y_i = f(x, y) B - f(x, y) BB $$

$$ Y_i = f(x, y) B - f(x, y) B $$  (13)

2) The above equations have their own focus on edge details preserving and noise attenuation. In order to synthesize the advantages of these three equations, by averaging the respective image edge obtain the final image edge. As shown in the equation (14),

$$ Y = \sum_{i=1}^{8} Y_i $$  (14)
After the above steps, because of interferences of environmental factors, part of the road area would be mistaken as non-pavement region. But on the premise of the detection of part road boundary, through the extension of the road route and the use of linear programming principle, we would get a more regular pure road region only include road and road information.

V. EXPERIMENTS AND RESULT ANALYSIS

In order to verify the validity of the proposed method, we selected the unstructured roads under different scenarios. Parts of images were derived from the real road test and other parts were downloaded from the internet. All the pictures were sorted into size 300×210. Experimental results were shown in Figures 5, 6, 7.

According to Figures (5, 6, 7), the experimental results showed that this proposed method can be used to detect campus road, water stains road and general earth road. According to Figure 5, when the road surface covered by a large area of shadow, this proposed method detected the road boundary accurately; According to Figure 6, this method was more accurate to realize the road boundary detection when the road surface covered by water marks. According to Figure 7, this kind of completely unstructured road, like general earth roads, could also be effectively implemented detection.
VI. CONCLUSION

Aim at the complicated unstructured road scene and easy to be interfered by environmental factors, a series of studies have been carried out in this paper. Take integrated analysis of the above test results, the conclusions are as follows.

A threshold segmentation algorithm based on minimum within-cluster variable exponent variance was constructed to realize the accurate segmentation of unstructured road. Because the exponent parameters were adjustable, this proposed algorithm could adaptively choose the exponent parameters according to the different shapes of the histogram. Therefore this method had a better environmental adaptability.

Using anti-noise morphological detection algorithm filtered image and extracted the road edge. This method avoided effectively the influence of external interference factors on the subsequent extraction of boundary line.

The proposed detection algorithm identified effectively unstructured road and have a better robustness under the influence of light and shadow, illumination changes, water stains and other adverse factors.

The algorithm still need to further perfection and improvement in the face of more complex environments. This paper did not take the road detection into account when the vehicle turns. Aim at this type of unstructured road, we need further research.

CONFLICT OF INTEREST

The author confirms that this article content has no conflict of interest.

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