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Real-time Road Congestion Detection Based on Image Texture Analysis

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Abstract

Proposing a fast detection algorithm for urban road traffic congestion based on image processing technology. Firstly, to speed up the processing and to freely select the interesting area, the human-computer interaction vehicle area detection was put forward. Then, by using the difference of texture features between congestion image and unobstructed image, proposing vehicle density estimation based on texture analysis. Through image grayscale relegation, gray level co-occurrence matrix calculation and feature extraction, the energy and entropy features that could reflect vehicle density were obtained from vehicle area. After features training, the decision threshold could be obtained and traffic congestion was carried out. Experimental results showed that the accuracy of algorithm was as high as 99%, and the processing speed could satisfy the real-time requirement in engineering. © 2016 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

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1. Introduction

Currently, the problem of road congestion becomes the national focus. Road congestions seriously affect people's normal travel, restrict the economical development of society, so this is a problem to be solved as soon as possible. With the wide use of traffic monitoring system, using video and image processing technologies to detect road congestion is attracting more and more interests [6].

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Through the continuous efforts of researchers, there is a set of relatively fixed process of road congestion detection based on image processing, which contains training monitoring background, road foreground detection, features extraction and training, road congestion estimation [2,5,8]. However, in this process, training background is time-consuming, and some factors can easily influence the result, such as scenes change, camera shaking, and the light changes.

But in reality, accurately obtaining traffic conditions in real time is the key to relieve road congestion. In this paper, a real-time road congestion detection algorithm based on texture analysis is proposed, which deals with image data from road surveillance systems and carries out the accurate identification of vehicle density in different scenes. It is considered to successfully provide quick and reliable traffic information to the traffic administrative departments.

2. Image Texture and Vehicle Density

Texture is a visual feature of images, it is formed by texture primitive according to certain statistical regularity or deterministic rules [4]. In other words, if the objects in image had similar sizes and appeared according to some rules, which means this image has significant texture characteristic. But if the targets had various kinds of size and appeared randomly, that means the texture feature is not significant. As shown in Fig.1, the texture of Fig.1. (a) is ordered, but the texture of Fig.1. (b) is chaotic. Because of this property, texture features are always extracted from images to estimate objects density, such as crowded people, fish school or other things [3]. When dense people appear in the scene, the texture feature of the image is obvious. The similar situation happens to fish school.

For traffic monitoring images, we can also consider to extract texture feature to estimate vehicle density. Although there are big cars and small cars, the shape of all cars is rectangular. When a cluster of vehicles driving by the lane line, it is sure that the area of cars has obvious texture feature, as shown in Fig. 2. So, we considered to extract texture feature to detect traffic congestion.

Several kinds of algorithms were proposed to quantify the texture feature of image, which can be divided into four categories: statistical analysis method, method based on model, method based on signal processing and method based on structure analysis. The most commonly used and most convenient is the method of gray level co-occurrence matrix (GLCM), which is based on second order statistics analysis [1]. GLCM reflects the second-order conditional probability distribution of pixel combination(*i*, *j*), which has specified direction θ and specified distance *d*. Normally, the value of θ is 0 °, 45 °, 90 ° or 135 °, *d* is set to 1. GLCM with different angle of θ could reflect texture feature on different directions. The size of GLCM is determined by the gray level of image. Generally, image gray level is 256, so the size of GLCM is 256×256. The computation of this kind of GLCM is time consuming and useless. Mostly, the gray level of original image is reduced to 16-color or 8-color. Fig. 3 shows the calculation of 8×8 GLCM, where $\theta = 0^\circ$, d = 1.



Fig.1. (a) image with ordered texture; (b) image with chaotic texture.



Fig.2. Crowded vehicles running along the lane line.

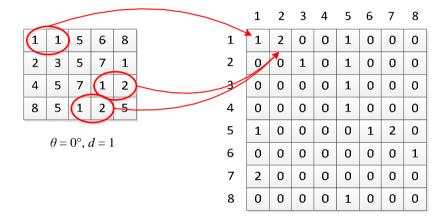


Fig.3. GLCM calculation.

It can be extracted a dozen kinds of features from GLCM, which respectively represent different texture, selecting certain feature to estimate object density needs to be seriously considered. For vehicle density estimation, we choose the energy and entropy features from GLCM. Because the energy shows whether the texture is thick or thin, if the image had thick texture, the energy value would be high. The entropy reflects whether the elements in GLCM are uniformly distributed. [7] proved that if the gray histogram distribution of image was uniform, the entropy feature would be high. For road traffic monitoring images, when there is large number of vehicles which are quite regularly running along the lane line, the gray histogram of image should be distributed uniformly and the texture of the image should be thin, therefore the energy feature value should be small and the entropy feature value should be big. In the opposite, if there are a few cars randomly running, the energy value should be big and the entropy value should be small. So, the value of energy is inversely proportional with vehicle density and the value of entropy is proportional with vehicle density.

According to the above theory, we put forward traffic congestion estimation based on texture feature extraction and training.

3. Proposed Approach

The algorithm proposed in this paper includes four steps, which are vehicle area calibration, GLCM calculation, feature extraction and road congestion recognition. The details are as follows.

3.1. Vehicle Area Calibration

As mentioned before, the current method of congestion detection basically carried out background training at first. However the proceeding is not only time-consuming, but easily affected by many factors. For time-saving, the paper proposed a fast method of human-computer interaction. That is artificially setting vehicle area firstly, and then using the texture analysis method for congestion estimation. After the setting, the gray value of vehicle area remains the same, while the other area is set to zero, which means the background. This approach is time-saving, at the same time the interesting area can be selected freely.

3.2. GLCM Calculation

The standard gray image is 256 gray scale, the corresponding GLCM is 256×256. Computing GLCM with this size is both time-consuming and not necessary. It is well known that mostly the colour of vehicle is single, so in image the gray value of vehicle should be single or several successive values. But because of the light reflection, actually the gray value of vehicle area may have dozen choices. It results in that GLCM histogram distribution is more homogeneous than real, therefore the extracted texture features cannot truly reflect the density of vehicles. To solve this problem, we can reduce the gray levels. After testing, it is suitable to reduce 256-level to 32-level. In 32-level image, the pixel value in the area of black vehicle only has less than 3 choices.

The GLCM can be calculated after gray scale reduction. In our approach, d is set to 1, that is to calculate the distribution of adjacent pixels. As for θ , we set four angles, which are 0°, 45°, 90° and 135°. These four GLCM can represent texture of different directions, including horizontal, vertical and diagonal direction. This method can be applied to deal with images taken from different places.

As mentioned before, after gray scale reducing the area with zero pixel value was treated as background. When carrying out texture analysis on the image, the background area should be abandoned. So, the first row and the first column of GLCM are removed. Consequently, the size of GLCM is changed from 32×32 to 31×31.

3.3. Features Extraction

We use Eq. 1 and 2 to extract energy and entropy feature from the four GLCM.

$$S_g(d,\theta) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} f(i,j|d,\theta)^2$$
(1)

$$S_{p}(d,\theta) = \left| \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} f(i,j|d,\theta|) \ln f(i,j|d,\theta|) \right|$$
(2)

In Eq. 1 and 2, f(i,j) is element of GLCM, L is the number of row or column of GLCM, which is 31, S_g is the energy and S_p is the entropy. Totally we can extract 8 features from all four GLCM, which are represented by vector \vec{s} , $\vec{s} = \{S_{g0}, S_{g45}, S_{g90}, S_{g135}, S_{p0}, S_{p45}, S_{p90}, S_{p135}\}$. We found that the value of S_g is one order of magnitude lower than the value of S_p , besides S_g is inversely proportional with vehicle density. So we use Eq. 3 to calculate new energy feature S'_g , which is one order of magnitude higher than S_g and is proportional with vehicle density. That is the same as entropy feature S_p . Our new feature vector is \vec{s}' , $\vec{s}' = \{S'_{g0}, S'_{g45}, S'_{g90}, S'_{g135}, S_{p0}, S_{p135}\}$

$$S_{g}'(d,\theta) = -\ln(\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} f(i,j|d,\theta)^{2})$$
(3)

Then we use Eq. 4 to calculate the final texture feature S, S is used to estimate vehicle density.

$$S = \frac{(S'_{g0} + S'_{g45} + S'_{g90} + S'_{g135})}{4} + \frac{(S_{p0} + S_{p45} + S_{p90} + S_{p135})}{4}$$
(4)

3.4. Road Congestion Recognition

Feature *S* reflects the density of vehicle in the image, bigger *S* means heavier road congestion, smaller *S* means unobstructed road condition. We carried out hundreds of experiments to obtain the decision threshold S_T . When $S > S_T$, there are crowded vehicles on the road, which may lead to traffic congestion. When $S < S_T$, the traffic is smooth. In the next section, the detail of obtaining threshold S_T will be introduced.

4. Experimental Results

The experiments were carried out on computer of 2.6GHz CPU and 4GB memory with Windows 7 operating system. The experimental data included two parts, some were downloaded from the Internet, and others were taken from self-made monitoring system.

First, 100 frame of crowded vehicles images and 100 frames of sparse vehicles images were chosen as samples. Two of them are shown in Fig.4.

Then, car area was celebrated and the results were shown in Fig.5.

Next, greyscale reduction and GLCM calculation were performed. Four GLCM with different direction θ were calculated from each image. Then energy and entropy features were extracted using Eq. 2 and 3. The eigenvalue *S* could be obtained by Eq. 4.

Now, a set of eigenvalue $\{S_i\}$ was got, where $i \in \{1, 2, 3, ..., 200\}$. Numeric statistical results showed the eigenvalue *S* of crowded and sparse vehicles was easily recognized. For most sparse vehicles images, *S* is less than 6. For most crowded vehicles images, *S* is bigger than 7. Therefore the decision threshold S_T was set to 6.5.

To test the accuracy of our algorithm, we dealt with another 100 frames of images randomly chosen from our data set. The result showed that 99 images were successfully estimated.





Fig.4. (a) sparse vehicles; (b) crowded vehicles.

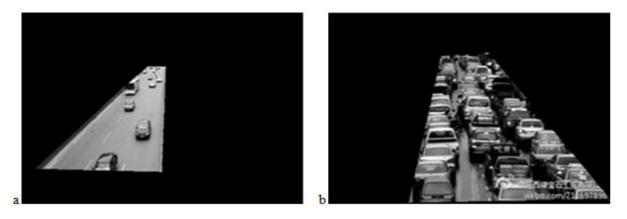


Fig.5. (a) detection result of sparse vehicles; (b) detection result of crowded vehicles.

For real-time testing, we selected a 60-second long traffic monitoring video, including 1500 frames. Because the monitoring scene was fixed, it only needed one time vehicle area calibration. The results showed it took 6,088ms to deal with this video, that is 4.059 frame per microsecond. The speed can completely satisfy the real-time requirement of engineering.

5. Conclusions

In this paper, a real-time traffic congestion estimation approach was proposed, which is based on image texture feature extraction and texture analysis. The main innovations are as follows. First, proposing human- computer interaction approach to set vehicle area. Which is not only faster than the common used background training method, but more convenient to select area of interesting. Second, we proposed extracting texture features to estimate vehicle density. Researchers have used texture analysis method to estimate the density of pedestrian and fish, but no one else used it to estimate the density of vehicle. Our experimental results showed using our new texture feature to estimate vehicle density, the accuracy could be as high as 99%, and the speed is very fast, which could meet the real-time demand in engineering. We believe that our approach would be integrated in road video surveillance system in the future and provide reliable and fast road information for traffic managers.

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