Journal of Artificial Intelligence Practice (2016) 1: 20-24
Clausius Scientific Press, Canada

Urban Road Congestion Recognition Using Multi-Feature Fusion of Traffic Images

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Keywords: Traffic condition recognition, Image processing, Feature extraction, Sift corner, BP neural network

Abstract: Traffic congestions happen more and more frequently on the current urban roads. Detecting the congestion rapidly and effectively can avoid the second damages. In this paper, we use the traffic images as data source instead of the videos to detect traffic congestions, which have the advantages of low cost and big probability to be applied widely. Firstly, the interest region of the traffic images are calibrated manually, and then the image features in the interest region are abstracted, including the sift corner, gray histogram variance, gray level co-occurrence matrix of energy and contrast. Finally, BP neural network is used to realize image multi-feature fusion, and to classify the traffic condition described by the traffic images. The simulation results show that the method can recognize the traffic condition with the accuracy of 95%.

1. Introduction

With the increase of the private cars, traffic congestion has become a serious social problem. Detecting the congestion rapidly is an effective way to avoid the second damage and improve the traffic efficiency of urban road net. The traditional traffic conditions are detected mainly by automatic test equipments, alarm emergency telephone and patrol vehicle, etc. At the beginning, loop is used to detect the traffic condition [1]. However, the installation and maintenance of loop not only influence road traffic, but also damage the road. Thus the microwave detector [2] appeared, which are installed in the sides of road. With the emergence of vehicle self-organizing network, vehicles [3] are used to collect traffic information. This method has the advantage of high precision of traffic condition recognition, but has the shortcomings of the high cost, high requirements of vehicle equipments, information disclosure, etc.

At present, the common traffic information collection method is based on video monitoring [4]. Surveillance videos have many advantages. They can provide a large amount of information and be seen directly. However, the video storage always costs big storage space and the traffic condition detection equipment based on monitoring videos are comparatively expensive. To overcome this problem, static images are used in this paper by sampling surveillance videos. And then image features are abstracted. Finally, a BP neural network was used to recognize whether there is the traffic congestion or not in a traffic image. Compared with the traffic congestion recognition method based on videos, this method not only keeps the advantages of videos, but also has the superiority of much less storage space and much lower cost.

2. Traffic image feature extraction

The flow chart of the algorithm in this paper is shown in Fig. 1. First, we extract the road region from traffic images by manual annotation. In order to eliminate the video differences resulted from the different installation angels of surveillance cameras, the geometric-correction is operated on the interested image region, and the result image is normalized to the size of 159x83. Then the extracted multi-dimensional image features are inputted to the BP neural network. Finally the traffic state appearing in an image is recognized by using the trained BP neural network. The key of the algorithm in this paper is the abstraction and election of the image features due to the fact that they have a direct effect on the recognition performance. The following features are chosen in this paper.

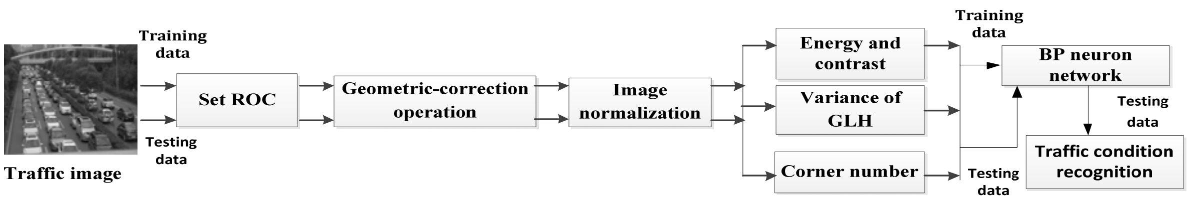

Figure 1. Flow chart of the algorithm

3. Contrast and energy feature of texture

Texture feature is an important appearance feature of images, and always used to represent regular structure involved in images. Different traffic images have different texture features. In the case of the congestion, there is many even textures in the images. In the case of the free traffic, there is less and uneven texture in the images. Texture feature in this paper is extracted by gray level co-occurrence matrix [5]. The gray level of original image is decreased to 8, therefore, the size of GLCM is 8x8. GLCM is calculated in four angles of 0^0, 45^0, 90^0 and 135^0. Additionally, the distance between the adjacent pixels is set to one. Contrast W_1 is defined as Eq.1, where $p(i,j)$ is the value of gray level co-occurrence matrix at (i,j). Energy W_2 is calculated by Eq. 2.

$$W_1 = \sum_{i,j} |i-j|^2 p(i,j) \quad . \tag{1}$$

$$W_2 = \sum_{i,j} p(i,j)^2 \quad . \tag{2}$$

When traffic is unobstructed, the gray distribution of road is uniform, consequently, the corresponding GLCM elements almost distribute in main diagonal, so the image contrast is low and the energy of images is high. When traffic is congested, the gray level of image have a wide range. The corresponding GLCM elements are distributed far from the main diagonal, so the image contrast is high, and the energy of images is low.

4. Variance of gray histogram

In the case of traffic jam, vehicles occupy a larger proportion than road. Therefore, when converting original image to gray image, the gray values have a wide range. In the case of smooth traffic, vehicles have a smaller proportion than roads. Hence, Different traffic condition have different gray distribution. The variance of gray histogram [6] is used to describe the gray distribution of traffic image, and the formula is described as follows:

$$\sigma^2 = \sum_{i=0}^{L-1} (i-\mu)^2 H(i) \quad (3)$$

Where σ^2 denotes variance of image, i is the gray level, L is 256, μ means the average of the gray value, $H(i)$ is the histogram value when the gray is i. For the congested image, the gray histogram have a wide range, thus the variance is large. For the unobstructed image, the gray histogram have a narrow range, then the variance is small.

5. Feature of corner number

When feature points are abstracted from the surveillance image, points of gray mutation in vehicles are much more than in road. So different traffic conditions have different numbers of feature points. In this paper, corner points extracted by sift operator [7] are the stable features of image. Moreover, sift have the advantages of scale invariant. Because the sift descriptor is a multi-dimensional vectors, there is no need to use it as feature actually. Therefore, the number of corners is considered as feature to identify traffic condition. When traffic is congested, the majority of image is road, and the number of corner is large. In contrast, when traffic is unobstructed, the small parts of image are vehicles, and the number of corner is small.

6. BP neural network model for traffic congestion identification

BP neural network [8] is a kind of multi-layer feed-forward neural network which is trained by error back-propagation algorithm. The structure of a BP neural network model is shown in Fig. 2. The BP neural network consists of input layer, output layer and hidden layer.

In this paper, the number of input nodes is ten. The output layer nodes are set two. neuron numbers of hidden layer can be obtained by Eq. 4.

$$I < \sqrt{m+n} + a \quad (4)$$

Where m represents the number of nodes in input layer, n denotes the number of nodes in output layer, a is a constant between zero and ten. According to Eq. 4, the neurons number of hidden layer is from four to fourteen. Next, BP models which nodes in hidden layer is between 4 and 14 are trained respectively. Table 1 shows that the model with nine nodes in hidden layer is optimal. Therefore, nine nodes in hidden layer is chose to recognize the traffic condition.

Table 1. BP neural network hidden layer node number and model error

Number of node in hidden layer	Testing error	Training error	Invalidation error
4	4.1113e-002	3.9874e-002	3.5155e-002
5	9.2136e-003	1.2011e-004	3.1241e-003
6	3.5488e-004	1.4323e-003	2.8376e-003
7	2.0293e-003	2.1345e-005	2.0293e-003
8	2.4722e-004	3.5432e-004	2.8978e-005
9	*6.7821e-005*	*8.6342e-005*	*2.9345e-008*
10	1.0034e-003	1.5639e-003	2.4119e-007
11	9.3345e-004	8.9041e-005	7.1186e-006
12	1.4785e-005	1.4538e-003	3.9243e-003
13	1.4213e-004	1.0082e-004	4.3875e-007
14	1.1234e-005	5.3456e-004	3.6433e-003

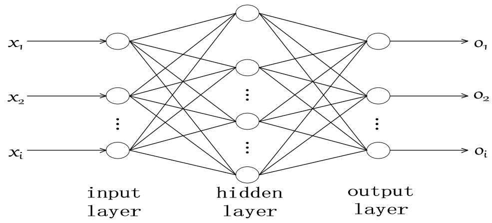

Figure 2. Structure of BP network

7. Simulations and analysis

In this section, to test the urban road congestion recognition using multi-feature fusion of traffic images, a series of simulations and experiments based on the matlab2010a platform have been carried out. At first, 10000 traffic images are took from the South Second Ring Road. 5000 images are selected as training sample, and the remaining images are as test samples,Then the neural network model which mentioned in section 3 is trained and tested.

Fig. 3 depicts the test result of BP neuron network, green stars represent the expect output of test sample, the red stars denote the real output of test samples. It is noticeable that the majority of actual outputs are consistent with expect outputs.

With regard to the evaluation of algorithm, the following two different measurements have been used: 1) the detection accuracy(DA) and 2) the detection recall(DR).

$$DA = TP/(TP + FP)\,. \tag{5}$$

$$DR = TP/(TP + FN)\,. \tag{6}$$

Where DA denotes accuracy, DR represents recall. TP is number that samples of class one are rightly classified to category one, FP is number that samples of class one are wrongly classified to category zero. FN is number that samples of class zero was wrongly classified to category one. After testing 5000 surveillance images collected from South Second Ring in Xi'an, the accuracy and recall of algorithm reach to 95% and 96% respectively.

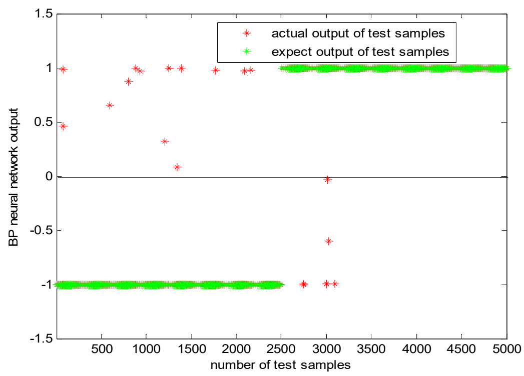

Figure 3. Test results of BP neural network

8. Conclusions

Images include rich information of traffic conditions and multi-feature are efficient to recognize the traffic condition. So taking advantages of them, we put forward an urban road congestion recognition algorithm using multi-feature fusion of traffic images. Compared with the method based on video, this method has the advantage of lower cost and lesser storage space. Besides, it also has short test time. Furthermore, the simulation results on the real data show our algorithm has superior traffic condition recognition performance. Specifically, the accuracy and recall of algorithm reach to 95% and 96% respectively. As a future work, we plan to abstract new features which can classify the traffic condition under various weather conditions. We can also optimize the recognition algorithm to improve the accuracy.

Acknowledgments

The authors acknowledge the support of the National Natural Science Fund of China (No.61572083), Provincial Natural Science Fund of Shaanxi (No.2015JQ6230), and the Special Fund for Basic Scientific Research of Central Colleges (No.310824152009). They furthermore thank the anonymous reviewers for valuable comments.

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