An automatic traffic-congestion detection method for bad weather based on traffic video

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Abstract: The result of automatic traffic-congestion detection method in bad weather is inaccurate. In response to this situation, we propose a detection method of traffic congestion based on histogram equalisation and discrete-frame difference. This method uses discrete-frame difference algorithm to extract the images that have vehicle information firstly. Then, the method employs histogram equalisation algorithm to eliminate the noise of the vehicle images. We also propose a corresponding traffic congestion index statistical algorithm in this step. After that, this method recognises vehicles from the video and computes the traffic congestion index. Finally, the method transforms the dimension of traffic congestion index and obtains the state of traffic congestion. It is proved by experiments that the method increases the accuracy rate of automatic traffic congestion detection in bad weather. This method has a wonderful prospect in some areas where there is usually bad weather.

Keywords: traffic congestion; histogram equalisation; video processing; inter-frame difference.

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1 Introduction

Traffic congestion detection is of great significance in road designing, traffic lights setting, preventing traffic congestion, automotive collision avoidance (Ma et al., 2012) and other application fields. Therefore, the traffic congestion detection plays an important role in transportation field. Unfortunately, the results of an automatic vehicle identification system for detecting traffic are prone to have a high false negative rate in bad weather such as fog, mist, and rain. It may cause errors in statistics of traffic congestion index and increase the risk or economic loss in relevant departments and industries (Mu and Zhang, 2013). Therefore, we designed and implemented a traffic-congestion detection method for bad weather to improve the accuracy of traffic congestion detection in bad weather.

2 Related work

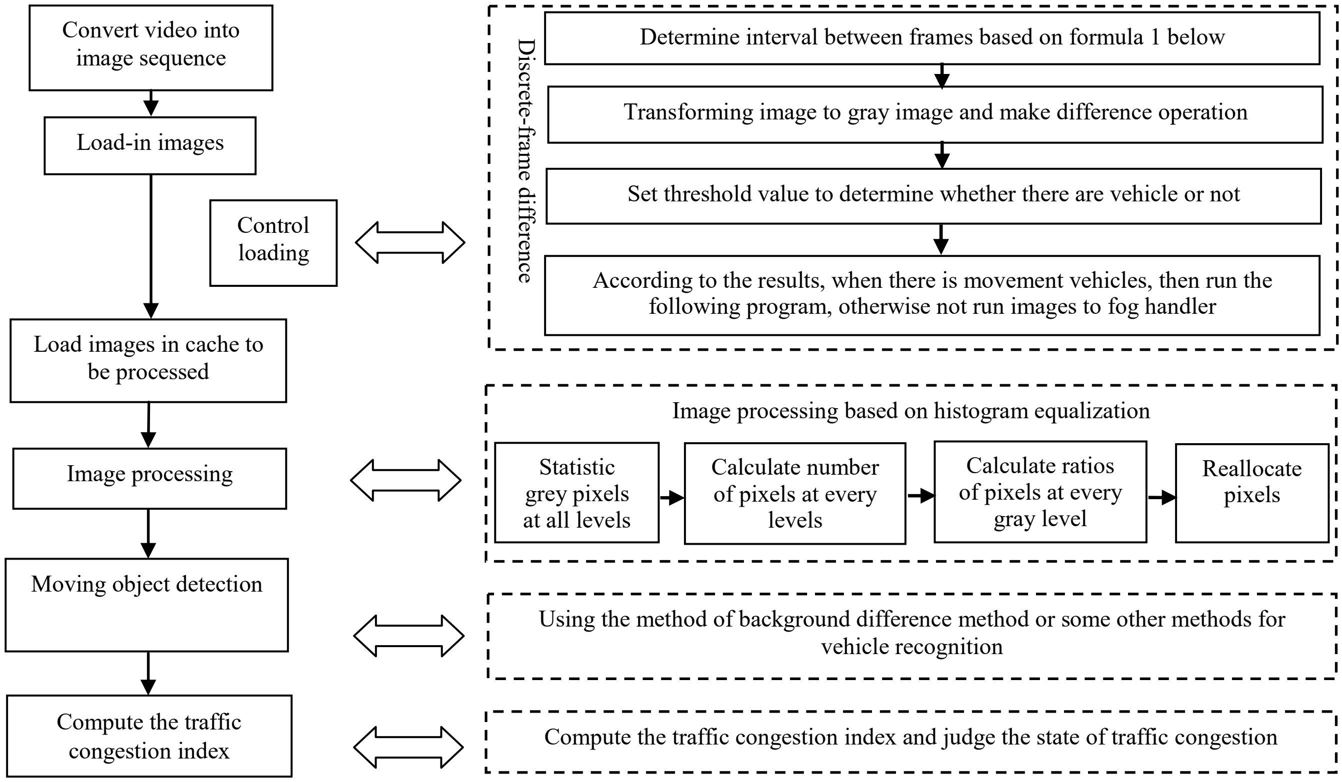
Traffic information acquisition-devices include contact traffic information acquisition-device and non-contact traffic information acquisition-device. Contact devices put the sensing device below the road. When the vehicle passes, sensors collect related data to obtain traffic information. Those methods have high accuracy, simple programs and simpler implements. On the other hand, their high economic costs, short life, complicated installation and maintenance restrict their developments. Non-contact detection devices do not require installation and maintenance and they are becoming more and more popular. Non-contact detection methods include wave frequency detection and video detection. The former method includes ultrasonic wave frequency detectors or infrared detection monitors. Video detection method processes the video recorded by the camera to obtain traffic information. Its installation and maintenance are simple. Especially, with the rapid development of video equipment and computer hardware, video-based traffic detection systems will be more widely used in some intelligent systems (Hechri et al., 2015; Song et al., 2015). Therefore, the traffic congestion detection method proposed by this paper uses video detection devices.

The automatic detection systems of traffic congestion based on video (Xia, 2013; He, 2009; Yang and Du, 2009) mainly use the methods of virtual detection line (Zhang et al., 1997; Zhao et al. 2013) vehicle tracking (Stark and Ihle, 1997; Zhao et al., 2013) or background subtraction nowadays. In the method of virtual detection line, a video measuring line is set on the top of each image. It can collect passing information of each vehicle and then recognise the vehicle. The matching method of the vehicle features finds the similarity between the characteristic of moving object and the characteristic of sampling vehicles, and compares the similarity with the threshold value to identify vehicles in the images. Background subtraction method recognises the vehicle by the subtraction between the current image and the background image obtained through Gaussian mixture models (Safi and Ashrafizaadeh, 2016). However, using only these methods cannot recognise the vehicles accurately in bad weather. It is necessary to add programs to increase the contrast of the images. Fortunately, there have been some methods, such as the dark channel prior method presented by He et al. (2010). It takes the minimum in the colour field and some fields firstly. After that, the images will serve as the dark channel of original images. It will increase the contrast by combining the light intensity and prior conditions finally. The neighbourhood average method is replacing the pixels with the average of points grey value in its neighbourhood. Some other effective methods (Ataman et al., 1980; Xie, 2009) are also based on it. There are also many methods such as the conversion based on retinex (Wang et al., 1999; Zia-ur et al., 1996) media fuzzy filter (Cover, 1991) or by readjusting brightness of images (Tarel and Hautiere, 2009). O'gorman (1998) gives the optimum definition of histogram equalisation (Wu, 2013). Now that machine learning is becoming more and more mainstream, some good algorithms can be used to detect and classify the vehicles (Fu et al., 2015, 2016; Gu and Sheng, 2016; Gu et al., 2007, 2015a, 2015b; Wen et al., 2015). Analysis of advantages and disadvantages of some popular image de-noising algorithms is present in Table 1. After analysing these methods above, we propose a new method to realise accurate detection of traffic congestion index in bad weather. Traffic congestion index is a conceptual index value that shows the degree of traffic congestion. There is no unified calculation method for traffic congestion index in current international. Experts and scholars presented many effective evaluation algorithms or protocols, such as the COC protocol presented by Fukumoto et al. (2007). This protocol of traffic congestion assessment is to use the operation data from the vehicle information real-time transmission to calculate the area of vehicle density. Then vehicle density will reflect the degree of the current traffic congestion. There is a voting protocol presented by Padron (2009) who regarded that driving condition of each car was likely to affect the transportation and operation of the whole area. Therefore, data of each car based on the speed of the vehicle driving must transfer to other vehicles. The congestion and the running status of each vehicle can be determined through the contrasts between data of different vehicles. What is more, many researches such as the ECODE protocol that shows the situation of traffic running based on traffic flow characteristics and presented by Maram and Azzedine (2015), etc. There is an evaluation method to calculate Beijing traffic congestion index proposed by Beijing traffic committee (Beijing Municipal Commission of Transport, 2014). It evaluates traffic congestion states through the data from real-time transmission of taxis, mainly considering the speed and the vehicle density. It realises the real-time monitoring of the city traffic condition. What is more, there are also some models (Yang et al., 2014) that evaluate traffic congestion and get good effects.

Table 1 Advantages and disadvantages of methods to image defogging

Algorithm	*Advantages*	*Disadvantages*
Histogram equalisation	The shortest time	Loss of grey levels
Conversion based on retinex	Better image processing effect on images with low brightness	Influenced by luminance
Media fuzzy filter	Big grey difference	Not suitable for real-time processing
Readjust brightness method	Good at treatment on light	Taking a long time
Dark channel prior	Stable and reliable	Taking a long time
Neighbourhood average	Suitable for real-time processing	May video delay

Figure 1 Process of the traffic congestion detection method in bad weather



3 Traffic-congestion detection method for bad weather

This paper uses the method of histogram equalisation to increase the contrast of images. Then the method alleviates the fuzziness caused by bad weather. Using improved inter-frame difference (discrete-frame method) to extract the video part that has vehicle information. It not only can save system energy but also make the whole system be fit for real-time processing. The paper first combines the histogram equalisation method and discrete-frame method, and presents a new calculation method of traffic congestion index.

3.1 Process of the traffic congestion detection method

The traffic-congestion detection method based on histogram equalisation and discrete-frame algorithms receives every image frame with a short memory. The next step is using discrete-frame method to recognise whether there are vehicles or not. To the images that have vehicle information, we use the histogram equalisation method to increase its contrast. Lastly, the method recognises vehicles and calculates traffic congestion index. The process of this method is illustrated in Figure 1.

As illustrated in Figure 1, the system is divided into several parts: video reading-in procedure, control-load procedure, image-processing procedure, vehicle detection procedure, traffic congestion index computing procedure. Among them, the video reading-in procedure makes the video load in image frames and store shortly. The controlling-load procedure loads the vehicle images into cache by using the discrete-frame difference method. The increasing contrast procedure makes the images more distinctly by using the method of histogram equalisation. The vehicle detection procedure recognises the vehicle information from the image sequences. The traffic congestion index computing procedure is to count the number of the vehicles and then computes the traffic congestion index. We will discuss the key technology of this method in the following.

3.2 Image extracting algorithm based on discrete-frame difference

Handling every frame of the video by inter-frame difference method (Takaba et al., 1982; Chen, 2014; Lin et al., 2008) in the bad weather to extract the vehicle images, system resources will be large occupied and it cannot be fit for the real-time processing. There is also no significance that we handle the video without vehicle information. Therefore, improving the inter-frame difference method, this paper presents a discrete-frame difference algorithm to save system energy and realise the extraction of vehicle images. The inter-frame difference method is making a difference calculation between the interfacing images. That is to say, this method analyse the motion feature by comparing the grey difference between interfacing frames. It can be preliminary determined when the grey difference is beyond the threshold value. In the meantime, the method loads the image frame into cache to increase its contrast by using histogram equalisation. In bad weather, vehicle speed is slow, and the time interval between every two frames is short. Therefore, vehicle-travelling distance is small between every two frames. Then, we can easily infer that we do not need to compute grey difference between every two frames. Therefore, the resources and time can be saved by intervening several interval frames. In order to guarantee that every car will be recognised, we give formula (1) to compute the number of interval frames in discrete-frame method.

$$Z < \frac{S_{space}}{V_{\max} \times t} \tag{1}$$

In formula (1), Z represents the number of interval frames. $V_{\max}$ represents the highest speed of vehicle. S_{space} represents time interval between every two frames. Occupied resources will be smaller by using the way of several interval frames. What is more, time will be shorter. We used the toolbox called Simulink to simulate this algorithm.

As illustrated in Figure 2, compute the grey-scale difference between background image and current image after inputting the image sequences. Then compare with the threshold value in a comparator to judge whether there is vehicle information in the current image. If the grey-scale difference is greater than the threshold value, we record this image frame. Otherwise, do not record it at all. If you want to achieve more frame difference apart, add a delay timer.

We can also calculate the sum of the pixels that are different from its former or next frame. After computing the interval number of frames, we can judge whether the current image contains vehicle information by the discrete-difference calculation method. As shown in formula (2), P (x, y) represents the pixel grey level difference. When the pixel points of the grey level difference are less than the pre-configured threshold value of T, c will be valued 0 in the processing. Otherwise b will be valued 1. In the end, in accordance with the formula (3), compute the sum of pixel points that are different from the background image roughly of current image.

$$P(x, y) = \begin{cases} 1 & c \geq T \\ o & c < T \end{cases} \tag{2}$$

$$S = \sum_{i=1}^{a} \sum_{j=1}^{b} P_{ij}(x, y) \tag{3}$$

When S is greater than the threshold value, we can deem that there is vehicle information in the current image. If S is less than the threshold value, we can deem that there is no vehicle information in the image and do not carry out image processing programs for this image.

3.3 Image processing algorithm of histogram equalisation

Histogram equalisation changes the condition that the grey level histogram of the original image is concentrated in some certain grey level internal. It redistributes image elements and improves the contrast of the image by putting some certain pixels of grey level in a similar state. Table 1 indicates that the method of histogram equalisation has advantages of low cost of time, less time complexity and less space complexity. Therefore, it is more suitable for real-time processing compared with other methods, so this paper proposes a method of using histogram equalisation to improve the contrast of the vehicle images. The algorithm is present in Table 2.

Table 2 Histogram equalisation program

Histogram equalisation program (realised in MATLAB 2014)
Input: vehicle images a.jpg
Output: after histogram equalisation images grey value of the corresponding matrix C
A=imread("a.jpg") // Read in the image a and deposited in the array
For k=0 to 255
B(k + 1) = length(find(A==k))/(m*n); /*The function called find can output where elements of the element to meet the requirements*/
End
For k = 1 to 256
For j = 1:k
S(k) = B(j) + S(k)
End
End
/*Using the formulas (Zhu and Cheng, 2012; Rafael and Richard, 2008) to equalise the histogram about the grey frequency of images. Among them, r_j represents grey level, B_r represents frequency of grey level, k represents there are k grey levels in the image, S_k represents the frequency of grey level after histogram equalisation.*/
For k = 1 to 256
S(k) = round((S(k)*256) + 0.5)
C(find(A==k)) = S(k + 1)
End for //update images pixels

3.4 Vehicle identification and calculation method of traffic congestion index

We can adopt visual detection line method, vehicle tracking method or background subtraction method. Virtual test line method sets a virtual detection line above the detection area described in the fifth and the seventh reference. Then, we can recognise and track the vehicle according to mutative intensity of test line. Tracking vehicle method presented in the sixth and seventh reference, which cuts the pixels to be consistent with vehicle characteristics in order to achieve identification and track of vehicle by matching vehicle characteristics. Background subtraction method, which this paper adopted, recognises the moving vehicles by making grey-scale difference between the current image and the background image.

Existing algorithms or protocols are not suitable for traffic congestion detection method based on discrete-frame difference, so this paper presents a method (traffic congestion index calculation method for discrete-frame difference) to calculate the traffic congestion index in bad weather. It assumes that there is no vehicle breaking down and the traffic-congestion index can be calculated through formula (7). Derivation process is as follows:

$$W = \sum_{i=1}^{k_1} C_i \tag{4}$$

$$W_{\max} = \frac{ST_{\max}}{zmt} \tag{5}$$

$$\rho_y = \frac{W}{W_{\max}} \tag{6}$$

In above formulas, W represents the total number of identified vehicles. k_1 represents the total number of frames of video section containing vehicle information. C_i represents the number of the vehicles identified in i frames in the video that has vehicle information. $W_{\max}$ represents the maximum number of identified vehicles. S represents the length of the video detection region. Z represents the number of interval frames in discrete-frame algorithm. $T_{\max}$ represents the total time of the video. t represents the difference of two frames. m represents the minimum length of a vehicle. ρ_y represents the traffic congestion index without unit conversion.

The calculation for traffic congestion index of discrete-frame difference method will set a threshold. It means that the minimum length of vehicles replaces real length of vehicles in the most congested state. Meanwhile, we regard no distance between vehicles as the most terrible state. That is to say, when the vehicle speed is high, the number of recognised cars will decrease and the traffic congestion index will decrease too. Therefore, the number of vehicles recognised in all frames can reflect the degree of traffic congestion accurately. Just because of this, the paper regards the quotient between the number of detected vehicles and the number of total vehicles in worst traffic congestion condition as traffic congestion index. It can reflect the degree of traffic congestion accurately. After the analysis of formulas (4) and (5) and the transformation of units, we can obtain formula (7).

$$\rho = 10m \times \sum_{i=1}^{k_1} \frac{c_i t Z}{ST_{\max}} \tag{7}$$

After calculating the traffic congestion index, we can judge the degree of traffic congestion based on its traffic congestion index. Table 3 shows the relation between traffic congestion index and the degree of traffic congestion condition.

Table 3 Relation between degree of traffic congestion and traffic congestion index

Traffic congestion index	*Degree of traffic congestion situation*	*Running condition*
0~2	Smooth	Fine
2~4	Barely smooth	Little fine
4~6	Mild congestion	Little worse
6~8	Moderate congestion	Worse
8~10	Severe congestion	Very worse

4 Experimental results

4.1 Images processing

We conducted the experimental test and data collection by using the traffic video data of reference 7 on MATLAB 2014a under Windows 7 system. The program runs in processing speed of 2.5 GHz dual-core CPU host. The running time of each algorithm are presented in Table 3, and their effects illustrated in Table 4.

Table 4 Running time comparison of different image increasing algorithms

Method	*Running time*
Histogram equalisation	7.7252 ms
Conversion based on retinex	40.7518 ms
Media fuzzy filter	25.3611 ms
Readjust brightness method	10.8834 ms
Dark channel prior	13.5112 ms
Neighbourhood average	20.9842 ms

Based on the effects of images processing and running time data of the above algorithms, we can obtain the conclusion that the running time of histogram equalisation is minimum and the image-processing effect conforms to the requirements for identifying vehicle. Under comprehensive consideration, histogram equalisation method is more suitable for images processing in automatic traffic-congestion detection system for bad weather.

4.2 Discrete-frame method

The paper designs the experiment to validate the efficiency of discrete-frame method. Using formula (1), we valued the interval frame number 3. Some results of screening on image sequences are illustrated in Table 6.

Time comparison between before discrete-frame difference and after discrete-frame difference is presented in Table 7.

Table 5 Effects comparison of de-noising algorithms

Methods	*Dark channel prior*	*Media fuzzy filter*	*Neighbourhood average*
Effects			
Methods	*Conversion based on retinex*	*Histogram equalisation*	*Readjust brightness*
Effects			

Table 6 Result of screening for video images by discrete-frame difference algorithm

	Running time	*Accuracy rate*	*Resources occupation*	*Algorithm complexity*
Traffic congestion detection method based on background subtraction	4.298 s	0.14	1	O(n)
Traffic congestion detection method based on discrete-frame difference	6.852 s	0.88	0.89	Between 2 O(n) and O(n)

Table 7 Time statistic of discrete-frame difference algorithm

Index	*Running time of discrete-frame method*	*Average time of histogram equalisation method on an image*	*Number of the whole video*	*Number of frames after running discrete-frame method*	*Saved time*
Times	2.055 s	0.234 s	120	31	18.771 s

Figure 2 Operation of the method based on background subtraction (see online version for colours)

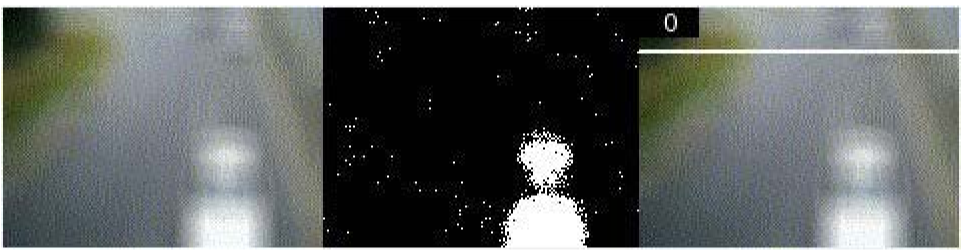


Figure 3 Operation of the method based on discrete-frame difference (see online version for colours)

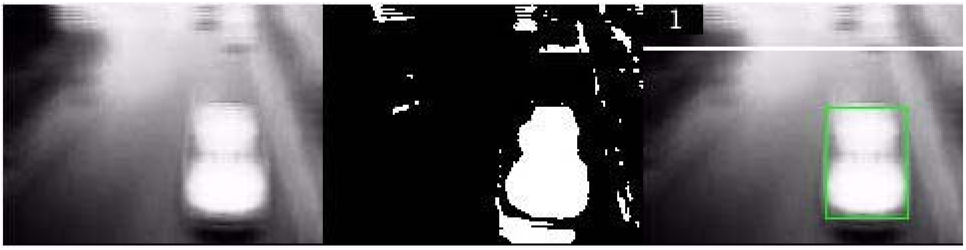


Table 8 Comparison of experimental data in two methods

	Running time	*Accuracy rate*	*Resources occupation*	*Algorithm complexity*
Traffic congestion detection method based on background subtraction	4.298 s	0.14	1	O(n)
Traffic congestion detection method based on discrete-frame difference	6.852 s	0.88	0.89	Between 2 O(n) and O(n)

Table 7 shows that the running time decreased roughly after using discrete-frame algorithm and achieved a good result.

4.3 *Vehicle identification*

We adopt the experimental data in the reference 7. In order to simulate bad weather, we carry out the fuzzy processing to the video. As illustrated in Figure 2, it is the operating condition of traffic-congestion detection methods based on background subtraction in bad weather. Figure 3 is the operating condition of traffic-congestion detection methods presented by this paper in bad weather.

We can see from Figure 2 that the detection results show more errors. Figure 2 shows the effect of the method proposed in the paper for the traffic congestion detection in bad weather. We can see that the latter is more suitable for bad weather. Table 8 shows the experiment results comparison of the two methods.

The calculation method for accuracy rate in Table 8 given in formula (8):

$$Z = 1 - \frac{\sum_{i=1}^{n} |C_i - E_i|}{E}, \left(n = \frac{T}{T_0} \right) \quad (8)$$

In formula (8), Z represents the accuracy of each method. T represents the total time of the video. T_0 represents the time interval between two adjacent video images. C_i represents the number of cars that is in the i^{th} video frame when recognising the car in video that has vehicle information. E_i represents the number of vehicles in the i^{th} frame of the video that has vehicle information actually. E represents the total number of vehicles that recognised in the traffic video. The ratio of the resources occupation in Table 8 refers to the ratio of processed occupation from video resources in cache in the two different methods.

The result of experiments shows that the threshold value is general to take 0.4 to 0.6, and if the number is higher, the accuracy of our detection method will be higher. Whether there is fog at that time or not, the greater the number, the smaller the possibility of miss checking. In bad weather, even if the current methods do not consider the causes mistakenly identified and make the value very small, ordinary method may miss vehicle information. In bad weather, our methods will have a lower false negative rate and wider applicable weather space by improving the decision threshold value.

Comparing the results of the detection methods, we can conclude that the advantages of our traffic-congestion detection methods are as follows:

1 Capturing images of vehicle information video by discrete-frame difference is faster than before. Shorter the time, less resource consumption, and higher operation efficiency.

2 We use the de-noising processing procedure based on histogram equalisation to eliminate the interference of bad weather causes. The image processing procedure can not only enhance the contrast of the image containing vehicle information but also decrease false negative rate. What is more, it increases accuracy rate of traffic congestion detection in bad weather.

5 Conclusions

In bad weather, the false negative detection rate of existing traffic detection methods is high, because of low visibility. To solve this problem, we research the current traffic-congestion detection methods and analyse the advantages and disadvantages of mainstream image de-noising algorithms. We propose a method for traffic congestion detection in bad weather. Firstly, we present the definition of discrete-frame difference algorithm, which can decrease the resource consumption of detection methods through extracting the images that have vehicle information. Then, we use the histogram equalisation algorithm to process vehicle images and decrease interference from bad weather. Finally, our method can recognise the vehicles in images and calculate the traffic congestion index. In a word, experiments and theoretical analyses show that this method decreases the false negative rate effectively and improves the accuracy of traffic congestion detection in bad weather.

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