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Road Traffic Anomaly Detection Based on Fuzzy Theory

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ABSTRACT The road traffic scenes are usually complex and the traffic video is vulnerable to external factors such as light, weather, and obstructions. It is difficult to extract the traffic parameters and detect the traffic anomaly exactly with the existing image processing and analysis technologies under such uncertainty factors. Considering the advantages of the fuzzy theory in dealing with uncertain information, we use the fuzzy theory to handle the complex issues in traffic video surveillance and put forward a traffic anomaly detection algorithm. First, the fuzzy traffic flow is designed based on the virtual detection lines and the fuzzy theory. Second, the fuzzy traffic density is designed based on the pixel statistics and the fuzzy theory. Third, the target's fuzzy motion state is designed based on the vehicle trajectory and the fuzzy theory. Besides, the relevant membership functions for these traffic parameters are designed to perform state evaluation. Finally, the traffic anomaly detection algorithm is designed based on above-mentioned fuzzy traffic parameters and fuzzy control rules. The experimental results show that the algorithm proposed performs well in road anomaly detection.

INDEX TERMS Fuzzy traffic parameters, traffic anomaly detection, fuzzy theory, video.

I. INTRODUCTION

With the development of traffic and video surveillance technologies, traffic management systems based on video surveillance have become widely used in traffic management. In the intelligent processing of traffic information, the detection and recognition of traffic anomalies such as anchoring, traffic congestion, traffic accidents and illegal driving have attracted the attention of many researchers due to its importance in traffic management. However, because of the complexity of traffic scenes, traffic surveillance video is vulnerable to external factors such as light, weather and obstructions. The limitations of existing image processing and analysis technologies make the traffic parameters (traffic flow, traffic density, vehicle trajectory, speed, etc.) based on traffic video very uncertain. As a result, currently it is very challenging to obtain high accuracy of the traffic anomaly detection by means of traffic parameters.

Considering the large amount of uncertain information existing in traffic surveillance video and the advantage of fuzzy theory in dealing with uncertain information, we propose a traffic anomaly detection algorithm for straight roads based on fuzzy theory. Our main contributions are as follows.

a) The fuzzy traffic flow is proposed. Traffic flow reflects the current traffic conditions and can be used to detect traffic anomalies. The traffic flow based on the virtual detection lines is obtained first and then membership functions are designed to obtain the fuzzy traffic flow.
b) The fuzzy traffic density is proposed. Traffic density reflects the current traffic intensity, which is very helpful for traffic anomaly detection. The traffic density based on the virtual detection lines is obtained first and then membership functions are designed to obtain the fuzzy traffic density.
c) The target's fuzzy motion state is proposed. Since our goal is detecting traffic anomalies, the target's fuzzy motion state is crucial. The target's trajectory is represented first and then membership functions are designed to obtain the target's fuzzy motion state.

d) The traffic anomaly detection algorithm is proposed. The proposed algorithm detects traffic anomalies by using the above-mentioned fuzzy traffic parameters and some designed fuzzy control rules. It can effectively detect traffic congestion and abnormal moving targets.

II. RELEVANT WORK

In recent years, the development of traffic surveillance video technology and its exuberant practical needs have attracted many researchers to conduct in-depth research on traffic anomaly detection. Seenouvong *et al.* [1] proposed a vehicle vision counting algorithm based on computer vision, which had high counting accuracy and improved the accuracy of traffic monitoring. Nowosielski *et al.* [2] proposed a new vehicle trajectory pattern recognition algorithm based on the Camshift algorithm, which can accurately analyze and identify the illegal parking or illegal turning of vehicles. Lin and Hsu [3] proposed the Superpixel tracking algorithm and vehicle trajectory analysis technology and applied them to crossroad traffic monitoring. Hai-Feng *et al.* [4] proposed a system for judging whether vehicles are retrograde and overspeed by detecting and tracking vehicle trajectories. Li *et al.* [5] used the method of extracting feature points to detect and analyze traffic anomalies with improved accuracy. Tan *et al.* [6] developed the sparse optical flow method to detect traffic anomalies such as retrograde and crossing roads. Ning *et al.* [7] jointly integrated various traffic information in anomalies analysis procedure, and it helped to achieve better applicability. Tageldin and Sayed [11] solved the problem of the collision of people and vehicles in highly congested traffic conditions, by virtue of judging the traffic situation through the distance between targets on the road within a certain time. Zhiyong *et al.* [8] successfully detect traffic incident of expressway scene by employing fuzzy logic by combining fuzzy logic and improved incremental comparison algorithms in their model. The model analyzes events by extracting vehicle speed and traffic flow information, but the premise of the model detection has certain limitations due to the complexity of traffic conditions. Liu *et al.* [9] used the GPS data of a city taxi, including trajectory and speed, to detect traffic congestion on urban roads. Although the accuracy of this GPS-based method is high, it has the disadvantage of high cost, which constrained its application. To address these issues, a new algorithm which integrates more traffic parameters is proposed in this paper. The proposed algorithm can not only detect traffic anomalies more accurately and meticulously, but also be effective to different situations.

III. TRAFFIC ANOMALY DETECTION ALGORITHM

A. THE FRAMEWORK OF THE ALGORITHM

Traffic scenes are often complex and diverse. In a traffic scene, there are areas unrelated to traffic, such as roadside trees and blue sky. In order to reduce these areas' impact on traffic information parameters and improve real-time performance, a trapezoidal area for traffic detection operations in traffic scene is delineate. The area is denoted as A. The shaded area in Fig.1 is the anomaly detection area A, and the upper left corner of the traffic scene is set as the coordinate origin O.

FIGURE 1. Anomaly detection area in traffic scene.

The overall framework of our algorithm is shown in Fig.2.

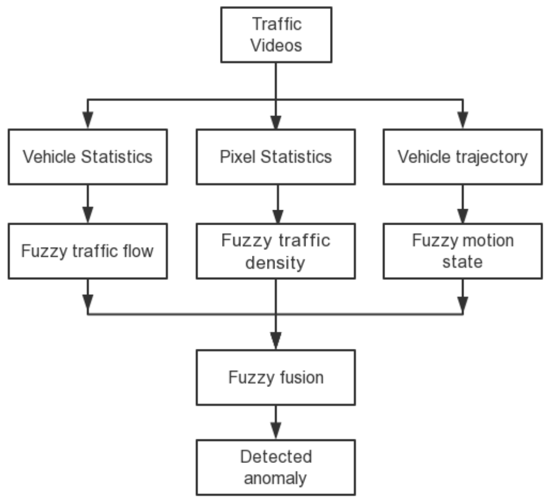

FIGURE 2. Framework of the traffic anomaly detection algorithm.

B. FUZZY TRAFFIC FLOW

The traffic flow reflects the current traffic conditions and can be used to detect traffic anomalies. Therefore, a new fuzzy traffic flow is designed in our work. The algorithm to obtain the fuzzy traffic flow is described in detail as follows.

Assuming that there are N lanes in a road, the unit time for statistics is T. $U_{nk}(n \in [1, N])$ is the number of vehicles of the n^{th} lane in the k^{th} unit time. In order to obtain the number of vehicles in each lane, a vehicle statistics method based on virtual detection lines is designed in this paper. Firstly, the foreground object information is acquired by using the Mixture of Gaussians (MOG) and background subtraction. Then, in the foreground detection area A, a virtual detection line is set for each lane. When a vehicle passes the detection line, U_{nk} will increase by 1. Then, the sum of vehicles on each lane in the k^{th} unit time denoted as traffic flow α_k, and it can be obtained as Eq.1.

$$\alpha_k = \sum_{n=1}^{N} U_{nk} \tag{1}$$

The Gaussian distribution model of traffic flow can be built for normal traffic in the period of K units of time.

Its expectation μ and variance σ^2 are given as follows.

$$\mu = \frac{1}{K}\sum_{k=1}^{K}\alpha_k \tag{2}$$

$$\sigma^2 = \frac{1}{K}\sum_{k=1}^{K}(\alpha_k-\mu)^2 \tag{3}$$

Subsequently, the traffic flow is analyzed according to the 3σ principles [13] and fuzzy logic. The 3σ principles are shown as follows.

$$\begin{cases} P(\mu-\sigma < \alpha_k \leq \mu+\sigma) = 68.3\% \\ P(\mu-2\sigma < \alpha_k \leq \mu+2\sigma) = 95.4\% \\ P(\mu-3\sigma < \alpha_k \leq \mu+3\sigma) = 99.7\% \end{cases} \tag{4}$$

Fuzzy sets L, M and H are used to represent the three states of the fuzzy traffic flow which are low, normal and high respectively. According to the 3σ principles, the membership functions of L, M and H shown in Eq.5-Eq.7 are designed. The membership function diagram is shown in Fig.3.

$$f_L(\alpha_k) = \begin{cases} 1, & 0 \leq \alpha_k < \mu-2\sigma \\ -\dfrac{\alpha_k}{\sigma}+\dfrac{\mu}{\sigma}-1, & \mu-2\sigma \leq \alpha_k \leq \mu-\sigma \\ 0, & else \end{cases} \tag{5}$$

$$f_M(\alpha_k) = \begin{cases} \dfrac{\alpha_k}{\sigma}-\dfrac{\mu}{\sigma}+2, & \mu-2\sigma \leq \alpha_k < u-\sigma \\ 1, & \mu-\sigma \leq \alpha_k < \mu+\sigma \\ -\dfrac{\alpha_k}{\sigma}+\dfrac{\mu}{\sigma}+2, & \mu+\sigma \leq \alpha_k \leq \mu+2\sigma \\ 0, & else \end{cases} \tag{6}$$

$$f_H(\alpha_k) = \begin{cases} 1, & \mu+2\sigma \leq \alpha_k \\ \dfrac{\alpha_k}{\sigma}-\dfrac{\mu}{\sigma}-1, & \mu+\sigma \leq \alpha_k < \mu+2\sigma \\ 0, & else \end{cases} \tag{7}$$

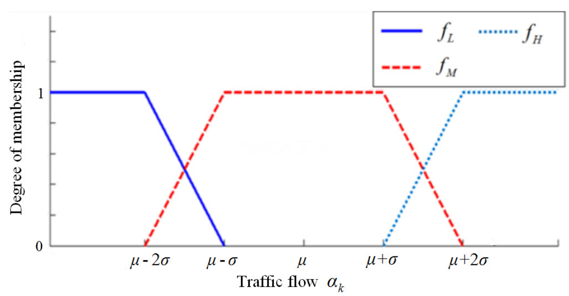

FIGURE 3. The membership function diagram of the fuzzy traffic flow.

From Eq.5 and Fig.3, it can be seen that the larger $f_L(\alpha_k)$, α_k is more likely to be *in* L. If $\alpha_k < \mu-2\sigma$, α_k belongs to L. If $\alpha_k \in (\mu-2\sigma, \mu-\sigma)$, α_k belongs to the critical state between L and M.

From Eq.6 and Fig.3, it can be seen that the larger $f_M(\alpha_k)$, α_k is more likely to be in M. If $\alpha_k \in (\mu-2\sigma, \mu-\sigma)$, α_k belongs to the critical state between L and M. If $\alpha_k \in (\mu-\sigma, \mu+\sigma)$, α_k belongs to M. If $\alpha_k \in (\mu+\sigma, \mu+2\sigma)$, α_k belongs to the critical state between M and H.

From Eq.7 and Fig.3, it can be seen that the larger $f_H(\alpha_k)$, α_k is more likely to be in H. If $\alpha_k \in (\mu+\sigma, \mu+2\sigma)$, α_k belongs to the critical state between M and H. If $\alpha_k > \mu+2\sigma$, α_k belongs to H.

C. FUZZY TRAFFIC DENSITY

The traffic density reflects the current traffic intensity, which is very helpful for traffic anomaly detection. Therefore, a new fuzzy traffic density is designed in our work. The algorithm to obtain the fuzzy traffic density is described in detail as follows.

In order to obtain the density of vehicles, a traffic density detection method based on statistics of pixel is designed. The algorithm binarizes the foreground image obtained by modeling a Gaussian mixture. Then the value of any pixel P_i is X_i ($X_i = 0$ *or* 1), the value of the pixels that make up the moving target is $X_i = 1$. Assuming that the number of pixels in the anomaly detection area A is α_{pix} and the traffic density is ρ_{pix}. Then the traffic density ρ_{pix} is obtained by using the following formula.

$$\rho_{pix} = \frac{\sum X_i}{a_{pix}} \tag{8}$$

where X_i is a pixel's value in A.

Since the traffic density ρ_{pix} of the k^{th} unit time can be obtained according to Eq.8, we also use Gaussian distribution to measure traffic density.

Fuzzy sets S, U and V are used to represent the three states of the fuzzy traffic density which are sparse, normal and dense. Then the membership functions of S, U and V shown as Eq.9-Eq.11 are designed. In Eq.9-Eq.11, ρ_1 and ρ_2 is the critical value between S and U, ρ_3 and ρ_4 is the critical value between U and V. The membership functions diagram is shown in Fig.4.

$$f_S(\rho_{pix}) = \begin{cases} 1, & 0 \leq \rho_{pix} < \rho_1 \\ \dfrac{\rho_{pix}}{\rho_1-\rho_2}+\dfrac{1}{\rho_2-\rho_1}, & \rho_1 \leq \rho_{pix} \leq \rho_2 \\ 0, & else \end{cases} \tag{9}$$

$$f_U(\rho_{pix}) = \begin{cases} \dfrac{\rho_{pix}}{\rho_2-\rho_1}+\dfrac{\rho_1}{\rho_1-\rho_2}, & \rho_1 \leq \rho_{pix} < \rho_2 \\ 1, & \rho_2 \leq \rho_{pix} < \rho_3 \\ \dfrac{\rho_{pix}}{\rho_3-\rho_4}+\dfrac{\rho_4}{\rho_4-\rho_3}, & \rho_3 \leq \rho_{pix} \leq \rho_4 \\ 0, & else \end{cases} \tag{10}$$

$$f_V(\rho_{pix}) = \begin{cases} 1, & 0 \leq \rho_{pix} < \rho_1 \\ \dfrac{\rho_{pix}}{\rho_4-\rho_3}+\dfrac{\rho_3}{\rho_3-\rho_4}, & \rho_3 \leq \rho_{pix} \leq \rho_4 \\ 0, & else \end{cases} \tag{11}$$

From Eq.9 and Fig.4, it can be seen that the larger $f_S(\rho_{pix})$ is, ρ_{pix} is more likely to be in S. If $\rho_{pix} \in (0, \rho_1)$, then ρ_{pix} belongs to S. If $\rho_{pix} \in (\rho_1, \rho_2)$, then ρ_{pix} belongs to the critical state between S and U.

From Eq.10 and Fig.4, it can be seen that the larger $f_U(\rho_{pix})$ is, ρ_{pix} is more likely to be in U. If $\rho_{pix} \in (\rho_1, \rho_2)$,

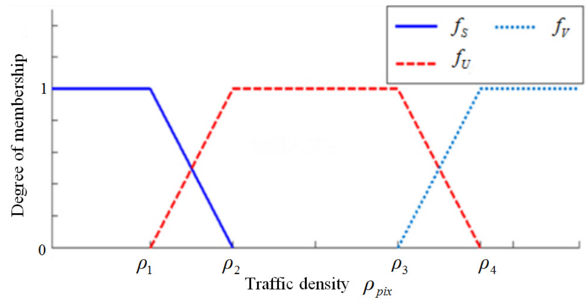

FIGURE 4. The membership functions of the fuzzy traffic density.

then ρ_{pix} belongs to the critical state between S and U. If $\rho_{pix} \in (\rho_2, \rho_3)$, then ρ_{pix} belongs to U. If $\rho_{pix} \in (\rho_3, \rho_4)$, then ρ_{pix} belongs to the critical state between U and V.

From Eq.11 and Fig.4, it can be seen that the larger $f_V(\rho_{pix})$ is, ρ_{pix} is more likely to be in V. If $\rho_{pix} \in (\rho_3, \rho_4)$, then ρ_{pix} belongs to the critical state between U and V. If $\rho_{pix} \in (\rho_4, 1)$, then ρ_{pix} belongs to V.

D. FUZZY MOTION STATE

When the traffic anomaly is detected, the trajectory of the target vehicle is in a changing state at each moment. It is difficult to define the motion state of the target vehicle by quantitatively outputting the displacement distance and the vector direction. Therefore, we design a new fuzzy motion state to measure the motion state of the moving target.

1) DISPLACEMENT VECTOR OF VEHICLES

In this paper, the trajectory of the target vehicle is obtained by extracting and tracking the target. In the normal traffic situation, assuming that the time of the target vehicle Obj passes through the detection area A is Δt. The trajectory of Obj in A can be described by its set of positions on each frame in the video, that is

$$\begin{aligned} Traj_{Obj} &= \{\mathrm{p}_1, \mathrm{p}_2, \cdots, \mathrm{p}_m\} \\ &= \{(x_1, y_1), (x_2, y_2), \cdots, (x_m, y_m)\} \end{aligned} \tag{12}$$

Where (x_1, y_1) is the starting point, and (x_m, y_m) is the ending point. For ease of calculation, the displacement vector from the starting point to the end point is used to approximate the trajectory of the target.

$$\overrightarrow{P_1P_m} = \overrightarrow{OP_m} - \overrightarrow{OP_1} \tag{13}$$

Where $\overrightarrow{OP_1}$ is the vector from the origin O to P_1, and $\overrightarrow{OP_m}$ is the vector from the origin O to P_{m}. Assuming x_s and y_s are the displacement component of the target Obj in different directions x and y, that are:

$$\begin{cases} x_s = x_m - x_1 \\ y_s = y_m - y_1 \end{cases} \tag{14}$$

According to the actual traffic situation, when $x_s \neq 0$, there is movement in the x direction, it may be cases that the vehicle normally changes lanes or a pedestrian/vehicle crosses the road. And when $y_s \neq 0$, it is indicated that there is movement in the y direction, it may result from normal driving or reverse driving.

Since there is a limitation in the range of the slope expression in a Cartesian coordinate system, the direction of the displacement vector $\overrightarrow{P_1P_m}$ is analyzed by using the angle θ between the x-axis and $\overrightarrow{P_1P_m}$. Assuming that r is the modulus value. θ and r can be calculated by Eq.15 and Eq.16.

$$\theta = \begin{cases} \arctan(\frac{y_s}{x_s}) + \pi, & x_s < 0,\ y_s \neq 0 \\ \arctan(\frac{y_s}{x_s}) + 2\pi, & x_s > 0,\ y_s < 0 \\ \arctan(\frac{y_s}{x_s}), & x_s > 0,\ y_s > 0 \\ 0, & x_s = 0,\ y_s = 0 \\ \frac{\pi}{2}, & x_s = 0,\ y_s > 0 \\ \frac{3\pi}{2}, & x_s = 0,\ y_s < 0 \end{cases} \tag{15}$$

$$\mathrm{r} = \sqrt{x_s^2 + y_s^2} \tag{16}$$

The lower boundary of A is $y = L$, and the direction of the traffic flow is along the positive direction of y-axis, the direction discussed in this paper is based on the straight direction. When $y_m > L$, it means that the target is driving or has been driven out of the detection area. Otherwise, it means that the target fails to exit the detection area normally.

2) FUZZY MOTION STATE

The fuzzy motion state mot_θ of the moving target Obj is in the following 4 situations: cross the road to the right(short for Ra), drive normally(short for Nm), cross the road to the left(short for La) and retrograde(short for Re). In other words, the fuzzy sets of the motion state of the target are Ra, Nm, La and Re. The corresponding membership functions are shown as follows.

$$f_{\mathrm{Ra}}(\theta) = \begin{cases} \frac{\sqrt{3}}{2}\tan\theta + \frac{3}{2}, & \frac{5\pi}{3} < \theta < \frac{11\pi}{6} \\ 1, & \frac{11\pi}{6} \leq \theta < 2\pi \ or\ 0 \leq \theta \leq \frac{\pi}{6} \\ -\frac{\sqrt{3}}{2}\tan\theta + \frac{3}{2}, & \frac{\pi}{6} < \theta < \frac{\pi}{3} \\ 0, & else \end{cases} \tag{17}$$

$$f_{\mathrm{Nm}}(\theta) = \begin{cases} \frac{\sqrt{3}}{2}\tan\theta - \frac{1}{2}, & \frac{\pi}{6} < \theta < \frac{\pi}{3} \\ 1, & \frac{\pi}{3} \leq \theta \leq \frac{2\pi}{3} \\ -\frac{\sqrt{3}}{2}\tan\theta - \frac{1}{2}, & \frac{2\pi}{3} < \theta < \frac{5\pi}{6} \\ 0, & else \end{cases} \tag{18}$$

$$f_{\mathrm{La}}(\theta)=\begin{cases}\frac{\sqrt{3}}{2}\tan\theta+\frac{3}{2}, & \frac{2\pi}{3}<\theta<\frac{5\pi}{6}\\ 1, & \frac{5\pi}{6}\leq\theta\leq\frac{7\pi}{6}\\ -\frac{\sqrt{3}}{2}\tan\theta+\frac{3}{2}, & \frac{7\pi}{6}<\theta<\frac{4\pi}{3}\\ 0, & else\end{cases} \quad (19)$$

$$f_{Re}(\theta)=\begin{cases}\frac{\sqrt{3}}{2}\tan\theta-\frac{1}{2}, & \frac{7\pi}{6}<\theta<\frac{4\pi}{3}\\ 1, & \frac{4\pi}{3}\leq\theta\leq\frac{5\pi}{3}\\ -\frac{\sqrt{3}}{2}\tan\theta-\frac{1}{2}, & \frac{5\pi}{3}<\theta<\frac{11\pi}{6}\\ 0, & else\end{cases} \quad (20)$$

From Eq.17 it can be seen that the larger $f_{Ra}(\theta)$ is, the greater the degree to which mot_θ belongs to Ra. If $11\pi/6\leq\theta<2\pi$ or $0\leq\theta\leq\pi/6$, then mot_θ belongs to Ra. If $\pi/6<\theta<\pi/3$, then mot_θ belongs to the critical state of Ra and Nm. If $5\pi/3<\theta<11\pi/6$, then mot_θ belongs to the critical state of Ra and Re.

From Eq.18 it can be seen that the larger $f_{Nm}(\theta)$ is, the greater the degree to which mot_θ belongs to Nm. If $\pi/3\leq\theta\leq 2\pi/3$, then mot_θ belongs to Nm. If $\pi/6<\theta<\pi/3$, then mot_θ belongs to the critical state of Nm and Ra. If $2\pi/3<\theta<5\pi/6$, then mot_θ belongs to the critical state of Nm and La.

From Eq.19 it can be seen that the larger $f_{La}(\theta)$ is, the greater the degree to which mot_θ belongs to La. If $5\pi/6\leq\theta\leq 7\pi/6$, then mot_θ belongs to La.If $2\pi/3<\theta<5\pi/6$, then mot_θ belongs to the critical state of La and Nm. If $7\pi/6<\theta<4\pi/3$, then mot_θ belongs to the critical state of La and Re.

From Eq.20 it can be seen that the larger $f_{Re}(\theta)$ is, the greater the degree to which mot_θ belongs to Re. If $4\pi/3\leq\theta\leq 5\pi/3$, then mot_θ belongs to Re. If $7\pi/6<\theta<4\pi/3$, then mot_θ belongs to the critical state of Re and La. If $5\pi/3<\theta<11\pi/6$, then mot_θ belongs to the critical state of Re and Ra.

E. TRAFFIC ANOMALY DETECTION

1) TRAFFIC CONGESTION DETECTION

In this paper, fuzzy traffic flow and fuzzy traffic density are used as two input parameters for traffic congestion fuzzy logic reasoning. The traffic condition output variable obtained by fuzzy logic inference is η. And we fuzz η to fuzzy sets Nc, Sc, Hc. The meanings of each fuzzy values are as follows: normal traffic(short for Nc), slight traffic congestion(short for Sc), heavy traffic congestion (short for Hc). And the relationship between the fuzzy traffic flow, the fuzzy traffic density and the output variable η is determined by the following fuzzy control rules which are obtained through experience and experiments.

From Fig.3 and Fig.4, we can see that each α_k and ρ_{pix} corresponding to the membership functions and either of them will result in no more than two simultaneous non-zero outputs of membership functions. The following discussion is made on the case where α_k and ρ_{pix} both belongs to two possible fuzzy sets.

$\exists\alpha_1,\alpha_2\in\{L,M,H\}$, α_k belongs to two possible fuzzy sets α_1 and α_2, and $f_{\alpha 1}(\alpha_k)\neq 0, f_{\alpha 2}(\alpha_k)\neq 0$.

$\exists\rho_1,\rho_2\in\{S,U,V\}$, ρ_{pix} belongs to two possible fuzzy sets ρ_1 and ρ_2, and $f_{\rho 1}(\rho_{pix})\neq 0, f_{\rho 2}(\rho_{pix})\neq 0$.

① If $\alpha_k\in\alpha_1$, and $\rho_{pix}\in\rho_1$, then η is η_{11}

② If $\alpha_k\in\alpha_1$, and $\rho_{pix}\in\rho_2$, then η is η_{12}

③ If $\alpha_k\in\alpha_2$, and $\rho_{pix}\in\rho_1$, then η is η_{21}

④ If $\alpha_k\in\alpha_2$, and $\rho_{pix}\in\rho_2$, then η is η_{22}

$f_{\eta 11}$ is the membership function of the output of α_1 and ρ_1 in Table 1. Analogously, $f_{\eta 12}$, $f_{\eta 21}$ and $f_{\eta 22}$ can be given, where $\eta_{11},\eta_{12},\eta_{21},\eta_{22}\in\{Nc, Sc, Hc\}$.

Because the fuzzy control rules connect the two conditions to "and," we use the minimum method to determine the membership functions of the four rules, as below:

$$\begin{aligned}f_{\eta 11}(\eta)&=\min\{f_{\alpha 1}(\alpha_k), f_{\rho 1}(\rho_{pix})\}\\ f_{\eta 12}(\eta)&=\min\{f_{\alpha 1}(\alpha_k), f_{\rho 2}(\rho_{pix})\}\\ f_{\eta 21}(\eta)&=\min\{f_{\alpha 2}(\alpha_k), f_{\rho 1}(\rho_{pix})\}\\ f_{\eta 22}(\eta)&=\min\{f_{\alpha 2}(\alpha_k), f_{\rho 2}(\rho_{pix})\}\end{aligned} \quad (21)$$

Finally, we defuzzify the output η. According to the attribute of η and Table 1, we group $f_{\eta 11}, f_{\eta 12}, f_{\eta 21}, f_{\eta 22}$ into set f_{Nc}, f_{Sc}, f_{Hc} and take the maximum value f_i of f_{Nc}, f_{Sc}, f_{Hc}. Set the road congestion coefficient to $C(C\in[0,1])$. w_i is the weight of f_i and the defuzzified output is calculated by Eq.22.

$$C=\frac{\sum f_i\times w_i}{\sum f_i} \quad (22)$$

TABLE 1. Fuzzy control rules of traffic congestion detection.

η	$\rho_{pix}\in S$	$\rho_{pix}\in U$	$\rho_{pix}\in V$
$\alpha_k\in L$	Nc	Nc	Hc
$\alpha_k\in M$	Nc	Sc	Sc
$\alpha_k\in H$	Hc	Sc	Sc

We use the calculated congestion coefficient C to determine that the actual traffic condition corresponds to the specific fuzzy value in η.

2) ABNORMAL DRIVING DETECTION

After the congestion coefficient C is obtained, it is used as a screening condition for anomaly detection of moving targets. Let the straight track set $l_s=\{Nm, Re\}$, cross track set $l_a=\{Ra, La\}$. If the motion state belongs to both l_s and l_a, we determine its motion state by the following equation.

$$pro=\frac{\lambda\times C\times f_s}{(1\text{-C})\times f_a} \quad (23)$$

where f_s, f_a respectively correspond to the membership function of the fuzzy motion state in l_s, l_a. And λ is the proportional coefficient.

When $pro \geq 1$, then mot_θ is the corresponding motion state in l_s. When the congestion coefficient is high, the traffic conditions at this time tend to be congested. So the probability of occurrence of the motion state in l_a will be reduced. That is to say, the closer pro is to infinity, the greater the degree of motion state belonging to l_s.

When $pro < 1$, then mot_θ is the corresponding motion state in l_a. When the congestion coefficient is low, the traffic conditions at this time tend to be normal. So the effect of congestion on detecting the motion state in l_a will be reduced. That is to say, the closer $pro$is to zero, the greater the degree of motion state belonging to l_a.

Finally, we detect whether the trajectory of the moving target is abnormal by the fuzzy control rules shown in Table 2.

TABLE 2. Fuzzy control rules of vehicle abnormal driving detection.

Final mot_θ	$mot_\theta \in Nm$	$mot_\theta \in Re$	$mot_\theta \in Ra$	$mot_\theta \in La$
$\eta \in Nc$	Nm	Re	Ra	La
$\eta \in Sc$	Nm	Nm	Ra	La
$\eta \in Hc$	Nm	Nm	Nm	Nm

F. STEPS

In summary, the traffic anomaly detection algorithm on the straight road in this paper is as follows:

Step 1: According to Eq.2 and Eq.3, we calculate the expected value μ and the variance σ^2 to train the initial Gaussian distribution model.

Step 2: Use the fuzzy traffic flow detection algorithm based on virtual detection lines and related membership functions to obtain the fuzzy traffic flow.

Step 3: Based on binarized foreground likelihood, fuzzy density parameter is obtained by Eq.8 and related membership functions.

Step 4: According to Eq.15, the vehicle trajectory representation method based on the virtual coordinate system is used to obtain the target's fuzzy motion state.

Step 5: Use fuzzy traffic parameters obtained in step 2-step 4 and fuzzy control rules to detect traffic anomalies.

IV. EXPERIMENTAL SETTINGS

In this paper, we use the one-way traffic video sequence SNA2014-Nomal recorded by us as experimental data to train the initial Gaussian distribution model and verify the algorithm by experimenting with different video scenes with video numbers 1 to 3. The relevant information of the SNA2014-Nomal video is shown in Table 3. The initial Gaussian distribution is shown in Fig.5.

In order to better demonstrate the applicability of the proposed algorithm, video sequences from three different scenes are utilized to experimentally verify the traffic anomaly detection. And we do experiments on the following three scenes.

TABLE 3. Training video SNA2014-Nomal's vehicle information.

Lanes	Frame number	Frame rate /second	Resolution	Average number of the vehicles	Standard deviation of the vehicle number
Lane 1	1.5×10^5	25	1440×1080	5.97	2.14
Lane 2	1.5×10^5	25	1440×1080	6.73	1.84
Lane 3	1.5×10^5	25	1440×1080	6.24	1.97
Total: 3	1.5×10^5	25	1440×1080	18.64	4.58

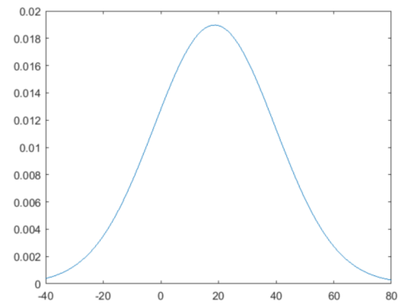

FIGURE 5. Initial Gaussian distribution.

A. SCENE 1

As shown in Fig.6, the traffic environment in Scene 1 is normal, but there are a number of traffic anomalies, such as retrograde and crossing the road.

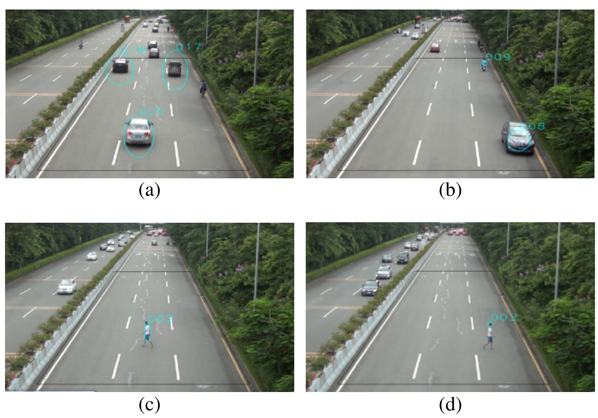

FIGURE 6. The normal and abnormal traffic screenshot in Scene 1. (a) Normal traffic. (b) Retrograde. (c) Cross the road to the left. (d) Cross the road to the right.

B. SCENE 2

As shown in Fig.7, there are multiple traffic congestion in Scene 2.

C. SCENE 3

The traffic conditions of Scene 3 are more complex. There are roads to different directions in front of the lane, where there

(a) (b)

FIGURE 7. The normal and abnormal traffic screenshot in Scene 2. (a) Slight traffic congestion. (b) Heavy traffic congestion.

FIGURE 8. The normal and abnormal traffic screenshot in Scene 3.

are many vehicles selecting lanes. Because the road is in the sun, changes in shadows and light also affect the detection.

The performance of the algorithm is evaluated with the accuracy rate (AR) and the false detection rate (FDR), which given by

$$AR = \frac{Correct\ detected\ abnormal\ events}{Actual\ abnormal\ events} \times 100\% \quad (24)$$

$$FDR = \frac{False\ detected\ events}{Total\ detected\ events} \times 100\% \quad (25)$$

where false detected events include both error detected events and missed detected events.

According to definition in Eq.24 and Eq.25, it can be understood that larger AR or smaller FDR means higher accuracy of our algorithm for detecting traffic anomaly events.

V. EXPERIMENTAL RESULTS AND ANALYSIS

We did experiments on the video sequences of the three scenes described above, and performed statistics and analysis on the experimental results, as shown in Table 4. Herein, Cr, Re, Sc and Hc stand for crossing, retrograde, slight congestion, and heavy congestion, respectively.

TABLE 4. Total detected traffic abnormal events in Scenes 1–3.

	Scene 1	Scene 2	Scene 3
Cr	6	13	12
Re	2	2	4
Sc	5	61	15
Hc	0	11	11

And in the experiment, the detection of traffic conditions is conducted for every 125 frames. Table 5 shows the total detected events in Scene 1-3.

TABLE 5. Total detected events in Scenes 1–3.

	Scene 1	Scene 2	Scene 3
Detected vehicles	341	1217	1757
Detections of traffic conditions	143	187	251

TABLE 6. Correct detected and actual abnormal events.

	Scene 1		Scene 2		Scene 3	
	N_correct	*N_actual*	*N_correct*	*N_actual*	*N_correct*	*N_actual*
Cr	6	7	0	0	0	0
Re	2	2	0	0	1	1
Sc	5	5	61	63	15	18
Hc	0	0	11	23	11	16

Then we compare the detection results with the actual situation and obtain Table 6, where *N_correct* and *N_actual* mean the correct detected and actual abnormal events, respectively. From Table 6, it can be seen that the correct detected and actual abnormal events show good agreement, which can demonstrate the validity of our algorithm.

Furthermore, based on the results in Table 4, Table 5 and Table 6, AR and FDR are calculated with Eq.24 and Eq.25 to measure the performance of our algorithm. The results are shown in Table 7.

TABLE 7. Accuracy rate and false detection rate results in Scenes 1 - 3.

	Scene 1		Scene 2		Scene 3		Average	
	AR (%)	*FDR* (%)	*AR* (%)	*FDR* (%)	*AR* (%)	*FDR* (%)	*AR* (%)	*FDR* (%)
Cr	85.7	0.29	\	1.07	\	0.68	**85.7**	0.68
Re	100	0	\	0.16	100	0.17	**100**	0.11
Sc	100	0	96.8	1.07	83.3	1.19	**93.4**	0.75
Hc	100	0	47.8	6.41	68.8	1.99	**72.2**	2.80

The results in Scene 1 show that our algorithm detected up to 100% events of interest in retrograde, slight congestion and severe congestion. The detection accuracy in crossing is also very high. This means that in the less complex traffic environment, our algorithm shows excellent accuracy in detecting traffic anomalies.

The accuracy of the proposed method is gradually lowered down when it goes to Scenes 2 and Scene 3 is significantly lower than that in Scene 1. This is because the clustering of the moving targets in the binary map will inevitably occur, when there are a lot of vehicles on the road and the traffic is in a congested state. Most systems will detect the aggregated multiple cars as one car, causing a decrease in traffic flow and interfering with the judgment of traffic conditions.

The innovation of our algorithm lies in the combination of traffic flow and traffic density. When the obtained traffic flow does not match the current traffic density level, the system will make comprehensive judgments according to the degree of match, which can effectively reduce the false detection rate. The experimental results in Scene 2 and Scene 3 show that our system also has false detection, but the false detection rate is relatively low.

In addition, in terms of detection of slight congestion, the average accuracy rate reaches 93.4%. The average accuracy rate in detecting heavy congestion is 72.2%. What's more, the average false detection rate of our algorithm in the four abnormal conditions is less than 3%, which also shows that our algorithm is quite robust in complex traffic conditions.

VI. CONCLUSION

In order to deal with a large amount of uncertainty information in traffic video surveillance, a traffic anomaly detection algorithm based on fuzzy theory is proposed. The algorithm uses fuzzy theory to fuse multiple traffic anomaly information to accurately detect traffic anomalies and solves the problem that it is difficult to deal with uncertainty information using deterministic theory and methods. And it makes up for the lack of high false detection rate and poor stability of single traffic information detection. Finally, experiments show that the algorithm proposed in this paper can accurately detect the traffic anomaly. It has high accuracy rate and strong robustness. It adds a new method for traffic abnormal intelligence detection.

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