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A Two-stage Traffic Sensor Location Method for Low-volume Road Incident Detection

Xiao-Feng Liu[1,2], Ji-Sheng Zhang[2], Ting-Ting Gao[1], Zhi-Wei Guan[1], Yu-Qing Song[1]
1. School of Automotive and Transportation, Tianjin University of Technology and Education, Tianjin 300222, China
2. Key Laboratory of Intelligent Transportation Systems Technologies, Ministry of Communications, Beijing 100088, China

***Abstract*—Low-volume road always lied at the area with few inhabitants and few traffic monitoring equipment, thus it's difficult to detect traffic incident and take traffic rescue in a timely manner. However, most research focused on high-volume road traffic sensor location for OD matrix estimation, travel time estimation and traffic volume estimation, not aiming to low-volume road for incident detection. Firstly, a two-stage traffic sensor location method was proposed for low-volume road incident detection, with the optimization objective of maximizing incident detection rate. At the first stage, high-resolution camera Automatic Vehicle Identification (AVI) was used to monitor closed road segments, at the second stage, video was used to monitor both the closed road segments and intersection segments. Then, reliability theory was adopted to model the incident detection rate of AVI and video parallel detection system. Next, a real-coded genetic algorithm was proposed to optimize the traffic sensor location problem. Finally, a case study was conducted and the case study result shows that incident detection rate of the first and second stage increase by 36.39% and 7.68% respectively, this demonstrates that the proposed method is effective.**

Keywords-low-volume road; incident detection; traffic sensor location; optimization; real-coded genetic algorithm

I. INTRODUCTION

In China western region, there are many low-volume roads, which have distinctive features of low traffic volume, lying at the area with low-density road network, few inhabitants and few traffic monitoring equipment. Taking Xinjiang autonomous region, China as an example, it is the largest provincial-level region with an area about 1.66 million square kilometers. Up to 2014, the mileages of highway, arterials and secondary arterials were 4 316, 1 254 and 13 894 kilometers respectively, and the road density was only 10.57 kilometers per 100 square kilometers. The average daily traffic volume of many highways was less than 5000 pcu [1], which was much lower than that of China eastern and central region highways. In addition, the majorities of highways in Xinjiang lie at areas with few inhabitants and traffic monitoring equipment. Once traffic accidents occur, it's difficult to detect them in a timely and rapid manner, and the prompt and effective actions could not be conducted to mitigate accident casualty and property loss. In recent years, with the advance of Western Development Planning, China is paying more investment on the construction and maintenance of traffic infrastructure, and the improvement of road safety in Western region. In this condition, how to locate traffic sensors properly and improve incident detection effectively for low-volume road, becomes an emerging problem.

In order to optimize traffic sensor location for incident detection, traffic incident detection algorithm and traffic sensor location purpose must be considered. As to traffic incident detection algorithm, there are several classical algorithms, such as California algorithm [2, 3], Standard Normal Deviate algorithm [4], Bayesian algorithm [5] and McMaster algorithm [6]. In addition, some artificial intelligent algorithms were developed in the past decades, such as artificial neural network algorithm [7], fuzzy logic algorithm [8], and so on. The aforementioned algorithms identify traffic incident based on the significant changes of macroscopic traffic flow parameters (such as speed, density and so on), which means that these algorithms are just suitable for high-volume road, not suitable for low-volume road because the traffic flow of low-volume road is hardly interrupted by any traffic incidents, and there doesn't exist significant change of traffic flow.

Regarding low-volume road, Fambro and Ritch [9] used loop detectors to conduct an input-output analysis of individual vehicles on a closed road segment, and proposed a low-volume algorithm. According to the vehicle speed and arrival time of the upstream road segment, the vehicle departure time of the downstream road segment was predicted, once a vehicle didn't arrive at the downstream in the pre-set threshold time, an incident occurrence was judged. However, there are two limitations of this low-volume algorithm. The first is that the distance between upstream and downstream loop detectors must be shorter than 800m, and the second is that this algorithm doesn't consider the road with intersections and is only suitable for closed road segment. Chang et al. [10, 11] proposed an incident detection method under low-volume condition using high-resolution camera Automatic Vehicle Identification (AVI) technique, analyzed the time-space relationship of vehicles passing different closed road segments, and studied the impact of AVI detection accuracy and road length on incident detection.

As to traffic sensor location purpose, most research aimed to high-volume roads (e.g. highways and urban freeways) and studied the traffic sensor location problem for three purposes. The first purpose is to estimate OD matrix, Yang and Zhou [12] used integer programming and heuristic algorithm to optimize loop detector location, Chootinan et al. [13] used multi-objective planning to optimize loop detector location, Castillo et al. [14] and Minguez et al. [15] proposed integer programming and rule-based criterion to optimize vehicle plate recognition device location. The second purpose is to estimate travel time, Chan and Lam [16] proposed a bi-level programming model, Liu et al. [17] used simulation test and evaluation, Viti et al. [18] minimized the volume error of unmonitored road segments, to optimize loop detector location. The third purpose is to estimate traffic volume, Hodgson [19] proposed a mixed two-objective model based on p-medium to deploy loop detector, Li et al [20] used simulation test and evaluation to deploy GPS floating car. In addition, only few research optimized traffic sensor location for incident detection. Liang et al. [21] used high-resolution camera AVI to detect incident for sparse low-volume road, and proposed a bi-objective optimization model to maximize the incident coverage and minimize the cost. However, the AVI detection accuracy and road intersections weren't considered.

In summary, most research aimed to high-volume road and optimized the traffic sensor location problem for OD matrix estimation, travel time estimation and traffic volume estimation, not aiming to low-volume road incident detection. However, few research studied the traffic sensor location for closed low-volume road incident detection, but road intersection and traffic sensor detection accuracy were not considered. Therefore, this paper will aim to detect low-volume road incident by using different types of traffic sensors, thus a two-stage traffic sensor location method for low-volume road incident detection is proposed.

II. TRAFFIC SENSOR LOCATION MODEL

A. Definition of low-volume road and traffic incident

The road with saturation less than 0.3 is defined as low-volume road, and its traffic flow is hardly interrupted and traffic congestion seldom happens even if traffic incident occurs. In high-volume road, traffic incident is always defined as an event (e.g., traffic accident, traffic congestion, stalled vehicle, road maintenance, parade or other special events), which will reduce road capacity or increase traffic demand obviously [22]. In this study, traffic incident of low-volume road is defined as the vehicle stopping behavior, including traffic accident, vehicle breakdown, as well as drivers' long-time rest along the road, which leads to significant vehicle travel delay.

B. Traffic sensor selection

In high-volume road, traffic incident is always identified by using loop detectors to detect traffic flow data and analyzing the significant changes of traffic flow parameters. For example, if the volume and speed decreased, or the density increased significantly in a short time, traffic incident is thought to occur. However, loop detector is not suitable for low-volume road incident detection because there is almost no traffic flow change.

Currently, Radio Frequency Identification (RFID) and AVI are always used to detect traffic incident both in high-volume road and low-volume road [23, 24]. As to RFID, an electronic tag is equipped with the vehicle, which records the vehicle information, such as vehicle user, vehicle type, vehicle plate number and so on. Once a vehicle passes through the roadside RFID reader in a given time period, the reader will read the vehicle information via wireless communication and the vehicle is confirmed. However, quiet few vehicles equip with RFIDs in low-volume road for the low-income level of vehicle owners and the lack of traffic infrastructure investment. As to AVI, AVI can catch the pictures of passing vehicles and recognize the vehicle plate numbers, then the vehicle plate numbers are compared at two neighboring AVIs, once the comparison doesn't match in the given time period, incident is thought to happen. However, if there are entrances or exits along the AVI segment (i.e., the segment is not closed and some vehicles run into or run off it), it's difficult to detect traffic incident by AVI method. Therefore, it is necessary to introduce video to detect incident both at the closed AVI segment and the intersection segment by monitoring traffic flow. Therefore, AVI and video are adopted to detect traffic incident for low-volume road in this study.

C. Model

Some assumptions are presented as follows:

(1) For the lack of traffic incident data of low-volume road, it is difficult to measure the distribution characteristics and severities of traffic incident, so it is an alternative way to use traffic accident substituting for traffic incident. Therefore, traffic accident prediction model is used to measure road safety and model traffic sensor location problem.

(2) Road fixed-length division method is used to divide the road into several sub-segments with fixed-length, and the number of traffic accident distributes along the sub-segment evenly.

(3) Generally, AVI incident detection precision is related to its technology performance, traffic volume, AVI installation interval, and weather condition [10, 11, 21]. For a specific low-volume road, the impacts of AVI technology performance and traffic volume on incident detection always remain stable, thus weather condition and AVI installation interval are the major influencing factors. In this situation, it is supposed that AVI works under normal weather condition, and AVI incident detection precision is mainly influenced by its installment interval.

(4) Both at the beginning and end of low-volume road, an AVI is installed respectively to monitor traffic flow. In addition, other AVIs are installed at the closed segments to avoid vehicle tracking failure, and videos are installed both at the closed segments and the intersection segments where vehicles run into or run off the road.

(5) If there is an intersection segment between two neighboring AVIs, the incident detection rate is supposed to be 0, because some vehicles run into or run off the segment, it's difficult for AVI to track incident vehicles. In order to avoid incident detection missing, correspondingly, video is used to monitor and detect traffic incident for the intersection segment.

Based on these assumptions, AVI location problem is described in Figure 1. In Figure 1, the road is divided into N sub-segments with the same length; the rectangle represents traffic accident number of each sub-segment, the higher the rectangle, the greater the traffic accident number is; the point represents AVI, there are m AVIs installed along the road, and two AVIs locate at the beginning and end of the road respectively; therefore, there are N fixed-length sub-segments, and there are m+1 AVI segments. Then, a two-stage optimization method is proposed to locate AVI and video respectively.

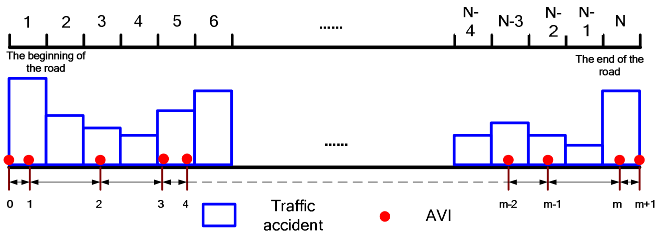

Figure 1. Distribution of traffic accident and AVI

(1) Stage I- AVI location optimization model

Suppose that the road length is L, the location of AVI installed at the beginning and end of the road is denoted as $x_0 = 0$ and $x_{m+1} = L$ respectively, and the AVI installation location set is denoted as $R = \{x_0, x_1, ..., x_m, x_{m+1}\}$. Additionally, suppose that there are n intersections along the road, the beginning position set of intersections is denoted as $Startpo\text{int} = \{p_1, p_2, ..., p_n\}$, and the end position set of intersections is denoted as $Endpo\text{int} = \{q_1, q_2, ..., q_n\}$, thus intersection position set is denoted as $Y = \{y \mid p_k \le y \le q_k, k = 1,2,...,n\}$. Furthermore, the AVI interval must be considered, if the interval is too large, it's difficult to detect incident in a timely manner, and if the interval is too small, more AVIs are needed and the cost would increase significantly, so the minimum and maximum AVI interval are denoted as $\Delta_{\min}$ and $\Delta_{\max}$ respectively.

The optimization objective is to maximize incident detection as follows:

$$\max\ Z = \sum_{i=1}^{m+1} A(i) \times f(x_i - x_{i-1}) \qquad (1)$$

The constraints are listed as follows:

$$c \cdot (m+2) \le C \qquad (2)$$

$$\Delta_{\min} \le x_i - x_{i-1} \le \Delta_{\max},\ \forall i = 1,2,...,m+1 \qquad (3)$$

$$x_i \notin Y, \forall i = 1,2,...,m+1 \qquad (4)$$

$$(x_{i-1} \le p_k) \wedge (q_k \le x_i) \rightarrow f(x_i - x_{i-1}) = 0, \forall i = 1,2,...,m+1; k = 1,2,...,n \qquad (5)$$

Where, $A(i)$ is the traffic accident number of m+1 AVI segments, $f(x_i - x_{i-1})$ is the mathematical function between AVI segment length and incident detection rate, which had been studied in [10, 11]. Eq. (2) is the cost constraint, c is the cost of an AVI, C is the total investment, and m+2 is the total number of AVIs installed. Eq. (3) is the AVI interval constraint. Eq. (4) ensures that AVI is installed at the closed road segment, not at the intersection segment. Eq. (5) means that the incident detection number is zero when two neighboring AVIs monitor an intersection segment, which corresponds to the 5th assumption. The decision variable is x_i, which is the AVI installation location.

As mentioned above, $A(i)$ is the traffic accident number of m+1 AVI segments, and its calculation steps are demonstrated as follows:

Step 1 Parameters setting

The traffic accident number between two neighboring AVIs is denoted as A(i) (i=1,2,…,m+1); the fixed-length of road division method is denoted as ΔL; the traffic accident number of different fixed-length segments is denoted as Accident(i) (i=1,2,…,N); the location of different AVIs is denoted as V(j) (j=1,2,…,m), and the accumulative accident number from the road beginning to the location of the jth AVI is denoted as aa(j) (j=1,2,…,m).

Step 2 Calculate aa(j)

① Calculate the location of the jth AVI on the fixed-length segments, and the upper integer segment number of the jth AVI is denoted as $E(j) = ceil(V(j)/\Delta L)$;

② When the jth AVI located at the first fixed-length segment, calculate its accumulative accident number as follows: $aa(1) = V(j) \times Accident(1)/\Delta L$;

③ In other conditions, calculate the accumulative accident number of the jth AVI as follows:

$$aa(j) = \sum_{i=1}^{E(j)-1} Accident(i) + (V(j) - \Delta L \times (E(j)-1)) \times Accident(E(j))/\Delta L.$$

Step 3 Calculate A(i)

① The traffic accident number of the first AVI segment is denoted as $A(1) = aa(1)$;

② The traffic accident number of the (m+1)th AVI segment is denoted as $A(m+1) = \sum_{i=1}^{N} Accident(i) - aa(m)$;

③ The traffic accident number of other AVI segments is denoted as $A(j) = aa(j) - aa(j-1), j = 2,3,...,m$.

(2) Stage II- Video location optimization model

Based on the AVI location result of stage I, videos are located at the intersection segments and the closed segments. It's prior to locate videos at the intersection segments, to monitor the traffic situation. Meanwhile, videos located at the closed segments can work with AVIs, which constitutes a parallel incident detection system to improve incident detection rate. Regarding this parallel incident detection system (i.e., AVIs and videos), reliability theory [25] is adopted to formulate its incident detection rate as follows:

$$D_{si} = 1 - (1 - D_i) \times (1 - \gamma) \qquad (6)$$

Where, D_{si} is the incident detection rate of this parallel system for the ith AVI segment; D_i is AVI incident detection rate for the ith AVI segment; and γ is video incident detection rate for the ith AVI segment.

Two video location scenarios are considered (shown in Figure 2), and the grid rectangle represents the video monitoring area. As video can rotate at 360 degrees to monitor road segment, it locates in the middle of grid rectangle in Figure 2. In scenario 1, video monitors the traffic situation of one segment; in scenario 2, video monitors the traffic situation of two segments.

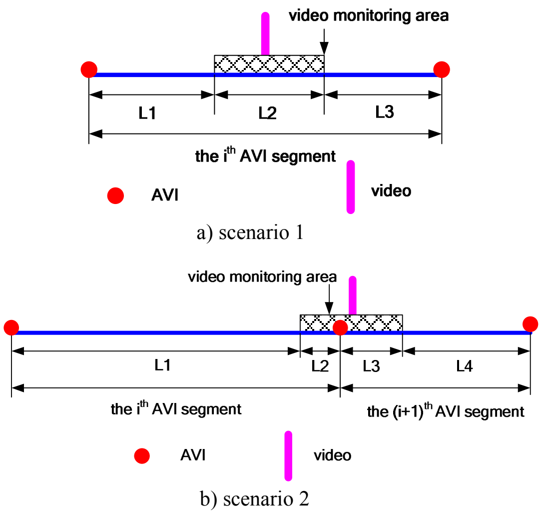

Figure 2. Two video location scenarios

In Figure 2, L1, L2, L3 and L4 are the length of different sub-segments respectively. In scenario 1, the number of accident detected at the ith AVI segment is formulated in Eq.(7); in scenario 2, the number of accident detected at the ith and (i+1)th AVI segment are formulated in Eq. (8) and Eq. (9) respectively.

$$\frac{L1+L3}{L1+L2+L3}\times Accident(i)\times D_i+\frac{L2}{L1+L2+L3}\times Accident(i)\times D_{si} \quad (7)$$

$$\frac{L1}{L1+L2}\times Accident(i)\times D_i+\frac{L2}{L1+L2}\times Accident(i)\times D_{si} \quad (8)$$

$$\frac{L3}{L3+L4}\times Accident(i+1)\times D_{s,(i+1)}+\frac{L4}{L3+L4}\times Accident(i+1)\times D_{i+1} \quad (9)$$

Where, $Accident(i)$ and $Accident(i+1)$ are the accident number of the ith and (i+1)th AVI segments respectively; D_i and D_{i+1} are the AVI incident detection rate of the ith and (i+1)th AVI segments respectively; D_{si} and $D_{s,(i+1)}$ are the parallel detection system incident detection rate of the ith and (i+1)th AVI segments respectively. When installing a video in scenario 1 and 2, the incremental number of accident detected can be formulated in Eq. (10) and Eq. (11) respectively.

$$\Delta D=\frac{L2}{L1+L2+L3}\times(D_{si}-D_i)\times Accident(i) \quad (10)$$

$$\Delta D=\frac{L2}{L1+L2}\times(D_{si}-D_i)\times Accident(i)+\frac{L3}{L3+L4}\times(D_{s,(i+1)}-D_{i+1})\times Accident(i+1) \quad (11)$$

Suppose that the number of accident detected in stage I is Z_0, the video monitoring radius is SD, the number of videos is n, the installation position set of videos is denoted as $Y=\{y_1,y_2,...,y_n\}$, L is the road length, and videos should be installed at the road mileage from SD to $L-SD$. Therefore, based on the AVIs location result of stage I, the optimization objective of stage II is formulated as follows:

$$\max H = Z_0+\sum_{j=1}^{n}\Delta D_j \quad (12)$$

Where, $\sum_{j=1}^{n}\Delta D_j$ is the incremental number of accident detected by installing videos, and the objective is to maximize the incident detection. The constraints include that: (1) the number of videos available; and (2) the minimum interval of two neighboring videos. The decision variable is the video installation position, once a video is installed along the road, its location scenario can be determined as scenario 1 or scenario 2, and then the Eq.（10）or（11）is adopted into the objective function.

III. ALGORITHM

The traffic sensor location problem aims to maximize accident detection rate, and its decision variable is the installation position of different traffic sensors. This is a typical nonlinear and discrete optimization problem, therefore, genetic algorithm is adopted. Considering that the decision variable is real number, a real-coded genetic algorithm is proposed to solve this problem, which consists of population initialization, fitness calculation, roulette selection & elitism, arithmetic crossover and non-uniform mutation.

Initial population is the installation position set of traffic sensors, it is generated as follows: (1) set the size of initial population; (2) generate m random numbers ranging from 0 to L (L is the road length, m is the number of traffic sensors installed) in each chromosome; (3) ensure that random numbers of each chromosome meet the installation interval constraint.

Objective function in Eq. (1) or Eq. (12) is adopted as the fitness function. If one chromosome doesn't meet the traffic sensor installation interval constraint, penalty weight is given to decrease its fitness. Each chromosome is assigned a fitness value, and the greater the fitness value is, the greater probability the chromosome has to be selected. Then, the elitist chromosome of the population is directly reserved to the next generation, and substitutes the worst chromosome, which is beneficial to improve algorithm convergence speed.

As the decision variable is the installation position of traffic sensors, arithmetic crossover is conducted to enrich the population diversity as the following steps:

(1) Set a global crossover probability and generate a random number at each iteration.

(2) Select two chromosomes randomly when the probability is greater than the random number, then select two exchange points of chromosomes and conduct chromosome linear combination. For example, two parent chromosomes $f_a = (x_1, x_2, ..., x_l)$ and $f_b = (y_1, y_2, ..., y_l)$ are selected and the exchange points are i and j, then the genes between the exchange points i and j are determined as follows:

$$\begin{aligned} x_k^{'} &= y_k \times \alpha + x_k \times (1-\alpha) \\ y_k^{'} &= x_k \times \alpha + y_k \times (1-\alpha) \end{aligned} \tag{13}$$

Where, α is a random number ranging from 0 to 1.

(3) Determine the new offspring chromosomes. Two new offspring chromosomes are determined as follows:

$$\begin{aligned} f_a^{'} &= x^{'} = (x_1, ..., | x_{i+1}^{'}, x_{i+2}^{'}, ..., x_j^{'} |, x_{j+1}, ..., x_l) \\ f_b^{'} &= y^{'} = (y_1, ..., | y_{i+1}^{'}, y_{i+2}^{'}, ..., y_j^{'} |, y_{j+1}, ..., y_l) \end{aligned} \tag{14}$$

Non-uniform mutation is conducted to enhance algorithm local search ability and population diversity as the following steps:

(1) Set a global mutation probability and generate a random number at each iteration.

(2) Select a chromosome randomly when the probability is greater than the random number and choose a mutation gene of the selected chromosome. For example, a parent chromosome $X^t = (x_1, x_2, ..., x_k, ..., x_l)$ is selected and the mutation gene is x_k.

(3) Determine the new offspring chromosome. The new offspring chromosome is expressed as $X^{t+1} = (x_1, x_2, ..., x_k^{'}, ..., x_l)$, where

$$x_k^{'} = \begin{cases} x_k + \Delta(t, U_{\max}^k - x_k), if\ random(0,1) = 0 \\ x_k - \Delta(t, x_k - U_{\min}^k), if\ random(0,1) = 1 \end{cases} \tag{15}$$

$U_{\max}^k$ and $U_{\min}^k$ are the lower and upper bounds of the variable x_k, and the function of $\Delta(t, y)$ is adopted as follows:

$$\Delta(t, y) = y \cdot (1 - r^{(1-t/T)b}) \tag{16}$$

Where, r is a uniform random number in the range [0, 1]; T is the iteration number; b is a system parameter in the range [2, 5].

IV. CASE STUDY

A. Test road and traffic accident prediction

A 225km long road segment of Korla-Kuqa highway in Xinjiang autonomous region, China with 9 intersections was selected as the test road to conduct case study, which volume was less than 5000 pcu per day in 2012, and it was a typical low-volume road. Research Institute of Highway Ministry of Transport, China had proposed a negative binomial accident prediction model for low-volume road, which used road fixed-length division method and recommended the fixed-length to be an interval ranging from 1 to 3 kilometers [26]. The model dependent variable was traffic accident prediction value of one road segment per year, and its independent variable included road million vehicle kilometers, average angle of horizontal curve, average angle of vertical curve, average slope of vertical curve, and truck percentage. In addition, the model correlation coefficient was 0.7973, and the test road was a low-volume road, therefore, the accident prediction model was adopted to conduct case study.

Based on above-mentioned, the fixed-length was chosen as 3 kilometers and the test road was divided into 75 sub-segments. Then the traffic accident prediction value of each sub-segment was calculated, and the number of predicted accidents was shown in Table 1.

TABLE I. NUMBER OF PREDICTED ACCIDENTS

	Min	**Max**	**Mean**	**St. Dev**
Number of predicted accidents (per year)	10.66	24.57	13.30	2.60

B. Scenario I: AVI location optimization

Currently, the video could turn around at 360 degrees to monitor traffic situation in many highways, and its monitoring radius can be as long as 500 meters [27]. Therefore, the minimum interval of two neighboring AVIs was set as 1 kilometer. As to the maximum interval of two neighboring AVIs, both the incident detection time and road minimum limited speed should be considered. In Korla-Kuqa highway, its minimum limited speed was 60km/h, moreover, incident should be detected in a timely manner for possible rescue, so the incident detection time was set as 15 minutes. Therefore, the maximum interval of two neighboring AVIs was set as 15 kilometers.

According to the proposed traffic sensor location method and the real-coded genetic algorithm, optimization was implemented at MATLAB platform. The parameters of real-coded genetic algorithm were set as follows: the population size was 30, the maximum generation was 500, the crossover probability was 0.6, the mutation probability was 0.08, and system parameter b of non-uniform mutation operator was chosen as 2, each optimization was conducted for 10 times. Then, changing the number of AVIs from 20 to 100, and the optimal incident detection rate was shown in Figure 3.

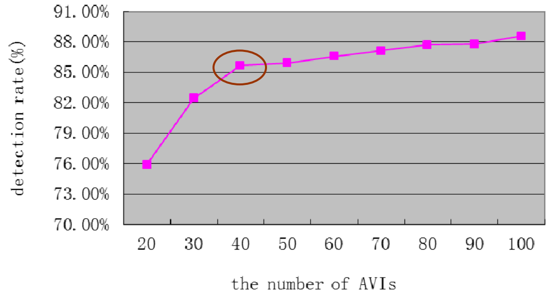

Figure 3. Detection rate with different number of AVIs

As Figure 3 shown, with the number of AVIs increasing from 20 to 40, incident detection rate increased dramatically, with the number of AVIs increasing from 40 to 100, incident detection rate increased slowly, thus the break point was 40 AVIs, and the corresponding incident detection rate was 85.65%. The optimization result was shown in Table 2.

TABLE II. OPTIMIZATION RESULT COMPARISON OF LOCATING 40 AVIS

	Minimum	**Mean**	**Maximum**
Initial detection rate/%	39.52	50.23	62.80
Optimized detection rate/%	82.39	84.49	85.65
Increase degree/%	+108.48	+68.21	+36.39

As Table 2 shown, the minimum, mean and maximum incident detection rates were improved significantly when locating 40 AVIs at the test road, and the increase degrees were 108.48%, 68.21% and 36.39% respectively. This demonstrates that the optimization is effective.

C. *Scenario II: video location optimization*

Based on the optimization result of locating 40 AVIs, video location optimization was conducted at the MATLAB platform and the parameters of real-coded genetic algorithm were set as follows: the population size was 30, the maximum generation was 500, the crossover probability was 0.6, the mutation probability was 0.08, and system parameter b of non-uniform mutation operator was chosen as 2, each optimization was conducted for 10 times. Then, changing the video incident detection rate (i.e., 100%, 85%, and 70%), and changing the number of videos from 5 to 30, the optimal incident detection rate was shown in Figure 4.

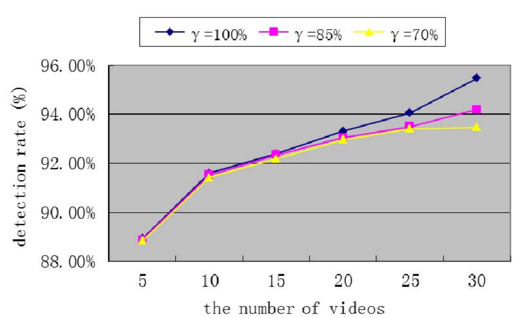

Figure 4. Incident detection rate with different situations

As Figure 4 shown, with the number of videos increasing, the incident detection rate increased gradually. With video incident detection rate equaling to 70%, 85% and 100%, the incident detection rate changed slightly when the number of videos was less than 15, and the incident detection rate changed significantly when the number of videos was 30. This demonstrates that both the video incident detection rate and the number of videos have impact on the incident detection result. When the number of videos was 30 and the video incident detection rate equaled to 100%, the optimal incident detection rate was 95.48%, and the traffic sensor location situation was shown in Figure 5.

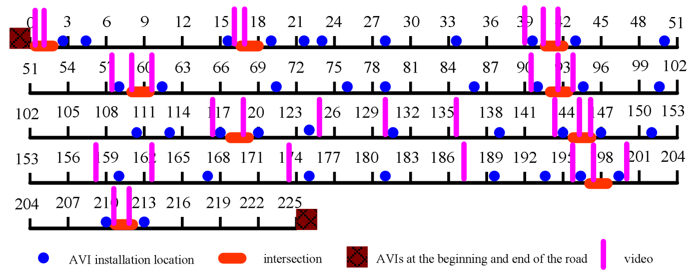

Figure 5. Diagram of locating 40 AVIs and 30 videos

As Figure 5 shown, 16 videos located at the intersection segments, and the other 14 videos located at the closed segments. If the incident detection rate is required to be not less than 95%, it is feasible to locate 40 AVIs and 30 videos based on Fig.5 and the optimization result was shown in Table 3.

TABLE III. OPTIMIZATION RESULT COMPARISON OF LOCATING 30 VIDEOS

	Minimum	**Mean**	**Maximum**
Initial detection rate/%	86.22	87.47	88.67
Optimized detection rate/%	92.55	93.92	95.48
Increase degree/%	+7.34	+7.38	+7.68

As Table 3 shown, the minimum, mean and maximum incident detection rates were improved to a certain extent when locating 30 videos, and the increase degrees were 7.34%, 7.38% and 7.68% respectively. As the incident detection rate of locating 40 AVIs was 85.65%, the incremental incident detection rate of stage II was 7.68%, this demonstrates that it's beneficial for incident detection improvement by introducing video to monitor traffic situation.

V. CONCLUSIONS AND DISCUSSIONS

This study selected AVIs and videos to detect low-volume road incident, and proposed a two-stage traffic sensor location method. The case study result shows that the incident detection rate is improved significantly after optimizing the location of traffic sensors, this demonstrates that the proposed method is effective.

The results are promising; however, the low-volume road safety level may be influenced by conducting traffic safety regulations and different weather conditions. Additionally, installing new traffic sensors and sensor detection accuracy have different impacts on incident detection. Therefore, it is a dynamic problem to locate traffic sensors for incident detection, and more factors should be considered to model traffic sensor location problem in further study.

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REFERENCES

[1] Transport Department of Xinjiang Uygur Autonomous Region. Statistical bulletin of road and waterway transportation industry development of Xinjiang autonomous region in 2014 [EB/OL]. [2015-12-22]. http://www.xjjt.gov.cn/article/2015-11-24/art84522.html.

[2] H. J. Payne, “Development and testing of incident detection algorithms,” Federal Highway Administration, Washington D C, USA, 1976.

[3] K. N. Balke, “An evaluation of existing incident detection algorithms,” Texas Transportation Institute, Taxas, USA, 1993.

[4] C. L. Dudek, C. J. Messer and N. B. Nuckles, “Incident detection on urban freeway,” Transportation Research Record. 1974, No. 495, pp.12-24.

[5] M. Levin and G. M. Krause, “Incident detection: a bayesian approach,” Transportation Research Record. 1978, No. 682, pp. 52-58.

[6] A. S. Willsky, E. Y. Chow, S. B. Gershwin, C. S. Greene, P. Houpt and A. L. Kurkjian, “Dynamic model-based techniques for the detection of incidents on freeways,” IEEE Transactions on Automatic Control. 1980, Vol. 25, pp. 347-360.

[7] R. L. Chew and S. G. Ritchie, “Automatic detection of lane-blocking freeway incidents using artificial neural networks,” Transportation Research Part C. 1995, Vol.3, pp.371-388.

[8] E. Chang and S. Wang, “Improved freeway incident detection using fuzzy set theory,” Transportation Research Record. 1994, No. 1453, pp.75-82.

[9] D .B. Fambro and G. P. Ritch, “Evaluation of an algorithm for detecting urban freeway 18 incidents during low-volume conditions,” Transportation Research Record. 1980, No. 773, pp. 31-39.

[10] Y.T. Chang, Q.Y. Liang, J.D. Sun and Z.R. Peng, “Traffic incident detection method for low-volume road based on vehicle tracking,” China Patent, 2011102533331. 2013.

[11] Y. T. Chang, Z. Su and Q.Y. Liang, “A new traffic incident detection method under low-volume condition based on automatic vehicle identification,” In Proceedings of the 9th International Conference on Fuzzy Systems and Knowledge Discovery, Sichuan, China, 12-16 June: pp. 29-31.

[12] H. Yang and J Zhou, “Optimal traffic counting locations for origin-destination matrix estimation,” Transportation Research B. 1998, Vol. 32, pp. 109–126.

[13] P. Chootinan, A. Chen and H. Yang, “A bi-objective traffic counting location problem for origin-destination trip table estimation,” Transportmetrica. 2005, Vol.1, pp. 65-80.

[14] T. Castillo, J.M. Menendez and P. Jimenez, “Trip matrix and path flow reconstruction and estimation based on plate scanning and link observations,” Transportation Research Part B. 2008, Vol. 42, pp. 455–481.

[15] R. Minguez, “Optimal traffic plate scanning location for od trip matrix and route estimation in road networks,” Transportation Research Part B. 2010, Vol. 44, pp. 282-298.

[16] S. Chan and H. K. Lam, “Optimal speed detector density for the network with travel time information,” Transportation Research Part A. 2002, Vol. 36, pp. 203-223.

[17] Y. Liu, X. Lai and G. L. Chang, “Detector placement strategies for freeway travel time estimation,” In Proceedings of the 2006 IEEE Intelligent Transportation Systems Conference, Toronto, Canada. 22-23 August; pp.17-20.

[18] F. Viti, W. Verbeke and C. M. J. Tampere, “Sensor locations for reliable travel time prediction and dynamic management of traffic networks,” Transportation Research Record. 2008, No. 2049, pp. 103-110.

[19] M. J. Hodgson and K. E. Rosing, “A network location-allocation model trading off flow capturing and p-median objectives,” Annals of Operations Research. 1992, Vol. 40, pp. 247- 260.

[20] Q. Q. Li, J. Yin and F. He, “A coverage rate model of gps floating car for road networks,” Geomatics and Information Science of Wuhan University. 2009, Vol. 34, pp. 715-718. (In Chinese)

[21] Q. Y. Liang, D. J. Sun, and Y. T. Chang, “Optimal location and combination of detectors for sparse road network,” In Proceedings of the 10th International Conference of Chinese Transportation Professionals, Beijing, China, 11-14 July; pp. 2109-2121.

[22] X. F. Liu, Z. R. Peng, H. J. Hou and L. Z. Wang, “Simulation and evaluation of using unmanned aerial vehicle to detect low-volume road traffic incident,” In Proceedings of the 94th Transportation Research Board of the National Academies, Washing D C, USA, 7-15 January 2015; pp. 801-816.

[23] J. Sun, Y. Yang and K. Li, “Optimization of automatic vehicle identification facility location for od matrix estimation,” Journal of Highway and Transportation Research and Development. 2010, Vol. 27, pp. 70-75. (In Chinese)

[24] T. Zhao, C. Guo and M. Jin, “A RFID based traffic information acquisition system and vehicle positioning method,” Journal of Electronics & Information Technology. 2010, Vol.32, pp. 2612-2617. (In Chinese)

[25] C. K. Kailash and L. R. Lamberson, “Reliability in Engineering Design,” New York: John Wiley & Sons Press, 1980.

[26] Z. Z. Tang, Y. He and T. Zhang, “Highway traffic safety manual,” Beijing: China Communications Press, 2007. (In Chinese)

[27] L. Hou, “High-resolution camera automatic vehicle identification system application on the Jin-li-wen highway in China,” China ITS Journal. 2012, Vol. 11, pp. 81-85. (In Chinese)