Acta Mech. Sin. (2011) 27(3):346–353
DOI 10.1007/s10409-011-0444-x

RESEARCH PAPER

Video-based measurement and data analysis of traffic flow on urban expressways

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Received: 22 October 2009 / Revised: 3 February 2010 / Accepted: 25 August 2010

Abstract A new video-based measurement is proposed to collect and investigate traffic flow parameters. The output of the measurement is velocity-headway distance data pairs. Because density can be directly acquired by the reciprocal of headway distance, the data pairs have the advantage of better simultaneity than those from common detectors. By now, over 33 000 pairs of data have been collected from two road sections in the cities of Shanghai and Zhengzhou. Through analyzing the video files recording traffic movements on urban expressways, the following issues are studied: laws of vehicle velocity changing with headway distance, proportions of different driving behaviors in the traffic system, and characteristics of traffic flow in snowy days. The results show that the real road traffic is very complex, and factors such as location and climate need to be taken into consideration in the formation of traffic flow models.

Keywords Traffic flow mode · Video-based · Vehicle recognition · Driving behavior · Snowy day traffic

1 Introduction

Traffic flow models are important tools to describe and investigate various complex traffic phenomena on expressways and road networks. They are also key elements in establishing traffic control systems. Actually, the design, utilization and evaluation of any automatic traffic system are all based on its traffic flow models for their capability of presenting the relationship among traffic flow variables. Generally, the formation of a traffic flow model relies on massive observation as well as in-depth analysis of real road traffic. Empirical data are indispensable to identifying parameters when the corresponding model is applied. One of the major demands of collecting such data is repeatability, i.e., a large amount of measuring needs to be conducted under nearly identical circumstances to output data and model parameters.

At present, traffic flow observations are mostly carried out via monitoring detectors, aerial photographing or just by manual counting. When it comes to large-scale road traffic, aerial photographing is a better way to measure traffic flow. When it comes to small-scale road traffic, detectors of various specifications are more frequently used. Generally, detectors are fixed along the roads or buried underground to measure the velocity or number of vehicles. Kerner [1–5], Helbing [6–9] and Knospe [10] used data obtained by detectors along highways to put forth non-linear velocity-density traffic flow models and a series of new concepts able to describe some complex traffic phenomena. However, common detectors can not collect all the data of a road section and installing these equipments needs extra funds. Aerial photographing techniques also have trouble with costs.

Traffic monitoring equipments are widely used. These equipments provide general information for the foundation of intelligent traffic systems and are capable of recording a large number of traffic flow data. Although not yet universalized, the method of collecting and analyzing road traffic data from recorded traffic videos has drawn wide attention. In this paper, a new traffic flow measurement is developed to establish relations between traffic videos and traffic flow models. The purpose is to obtain velocity-headway distance data pairs which have better simultaneous characteristics and

The project was supported by the National Natural Science Foundation of China (10772050).

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are easy to transform into velocity-density and flow-density data pairs for further research. This measurement can efficiently collect traffic flow parameters so as to help promote the theoretical research of traffic flow models.

2 Measurement design

2.1 Traffic video recording

To simulate the working process of the monitoring equipment, a camera was set somewhere above the road (usually on overpasses or roadside buildings) to shoot continuously for a period of time ranging from a few quarters to a few hours. Then the video file was transformed into sequential images with the time interval between every two consecutive images being 0.8 s. (The scanning frequency of a digital camera is 25 frames per second, so 0.8 s takes up 20 frames.)

2.2 Data collecting

In every image a pair of adjacent vehicles can be located to obtain the headway distance between the two. The displacement and mean velocity of the following vehicle during the time interval can also be acquired. By doing this to all the images, a large number of velocity-headway distance data pairs can be collected. A semi-automatic program (Fig. 1) with an interactive interface has been designed to collect velocity-headway distance data pairs. The size of the windows is proportionally configured and a magnifying window is added for convenience. The steps of manually data collecting are as follows:

(1) Locate the head position of a random vehicle n on image i (Fig. 1a);

(2) Locate the head position of n's preceding vehicle $n+1$ on image i;

(3) Locate the head position of vehicle n on image $i+1$ (Fig. 1b).

Through (1) and (2), the headway distance of n can be obtained. Through (1) and (3), the displacement of n can be obtained. The velocity of n can also be obtained since it equals the ratio of displacement to time interval. By following the above steps repetitively, one can collect numbers of velocity-headway distance data pairs from the image sequences.

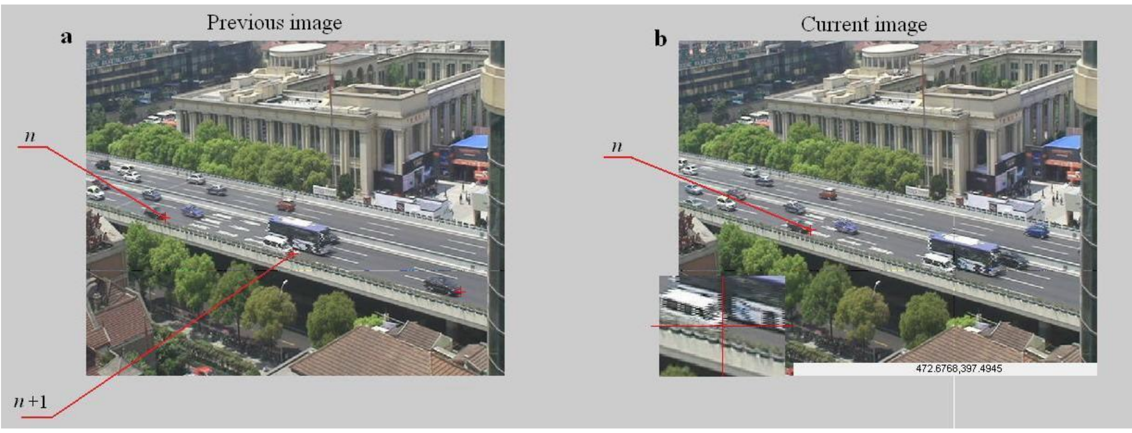

Fig. 1 Interface of the program designed to collect data pairs

2.3 Automatic vehicle detection

An automatic vehicle detection system has also been developed which needs very small amount of calculation and manages to capture as much onscreen traffic flow data as possible. The system is intended to collect data pairs by applying one-dimensional gray-level scanning line technique. This method does not demand so much image processing as those two-dimensional vehicle detection techniques, because only a small region of image is searched for its gray-level value and the whole process of detection becomes very simple. The output of the system is in the form of velocity-headway distance data pairs. The scanning line is set parallel to the lane lines of the road.

The images directly extracted from the video file were all transformed into gray-level images. The gray-level value evaluates brightness, and vehicles in the image are significant local changes of brightness, which is an important feature for vehicle recognition. When vehicles move throughout the image, the gray-level value of the background changes very little. Automatic background extraction method is used to acquire a background image in advance. The algorithm traces small changes of road illumination, and if the difference between the compared images is large, background image updating will be initiated. In addition, road illumination and vehicle shadows are taken into consideration when the system is set up.

The image's coordinate system is set as follows: the x-axis is the horizontal axis, the y-axis is the vertical axis and the origin is at the top left corner of an image. When an image $I(x, y)$ (which indicates the gray-level value of all the pixels in this image) is input, the algorithm subtracts the gray-level value of each pixel along the scanning line l_s in $I(x, y)$ from that of each corresponding pixel on the background image $B(x, y)$ (which indicates the gray-level value of all the pixels in the background image). In this process, if a pixel of salient brightness change is found (its absolute gray-level difference

$$|B(x, y) - I(x, y)| > \theta, \quad (x, y \in l_s), \tag{1}$$

where θ is a threshold, usually 50% of the value of $B(x, y)$), it is labeled as a start point. Then its next 15 neighboring pixels are compared in sequence with $B(x, y)$in the same way and those whose absolute difference is greater than θ are counted. If the total number is more than 9, this start point is recognized as the head position of a potential vehicle. Otherwise, the scan continues from the next pixel. Once a start point is acknowledged, the scan starts again searching for the vehicle's possible rear position. Similarly, when a pixel of salient brightness change is followed by 9 out of its 15 neighbors which meet the discriminant of

$$|B(x, y) - I(x, y)| < \theta, \quad (x, y \in l_s), \tag{2}$$

it is labeled as an end point. The region between these two points is hypothesized to contain a passing vehicle. The same procedure continues until the boundary of an image is reached. Figure 2 shows the gray-level value of the pixels along the scanning line in two consecutive images.

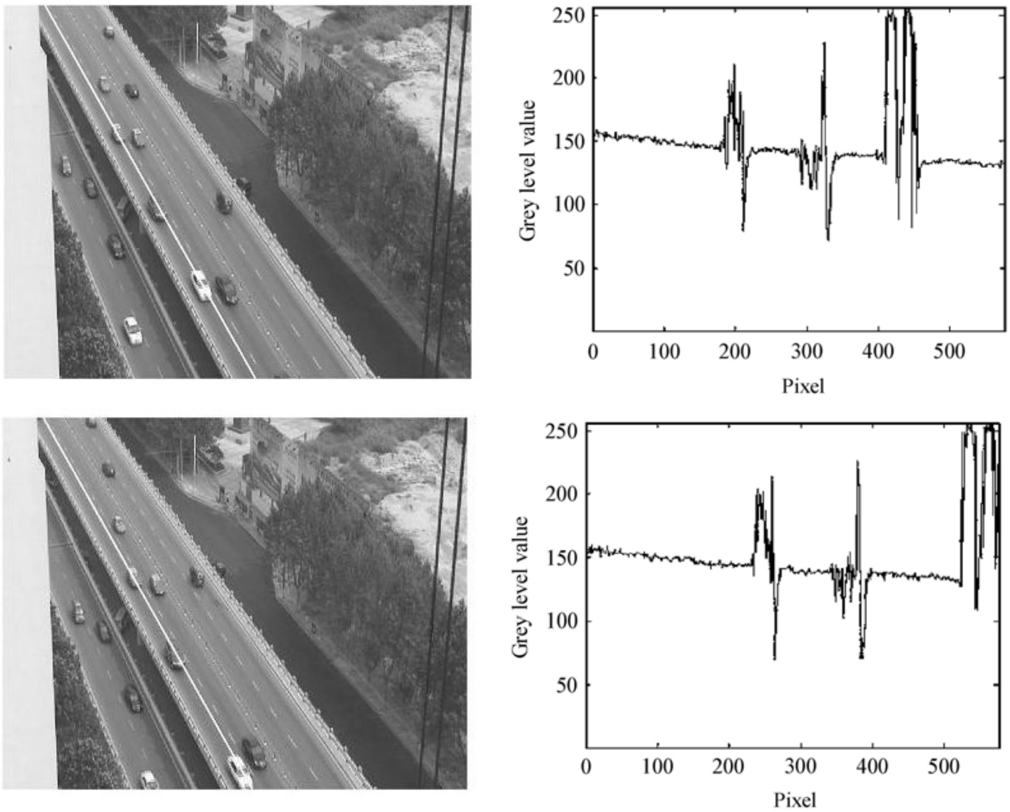

Fig. 2 Movement of vehicles along the scanning line

2.4 Error estimation

The error caused by this measurement is estimated in this part. Assume that a vehicle covers L meters during t seconds between any two consecutive images. Then the velocity of the vehicle should be $V = L/t$. However, possible errors may be brought about during the process of vehicle recognition, in which case the distance becomes $L' = L + \Delta x$ and the velocity becomes $V' = L'/t$. If the absolute error of distance caused by inaccurate vehicle detection in two consecutive frames goes up to 0.5 m, that of the velocity comes up to 2.25 km/h, while a maximum absolute error up to 3 km/h is generally allowed in traffic engineering. In that case, as long as the absolute error of distance is kept within 0.5 m, the overall absolute error is acceptable.

3 Data statistics

By means of the aforementioned semi-automatic program and one-dimensional gray-level scanning line technique, over 33 000 data pairs have been collected from the video files recording expressway traffic of Zhengzhou Jinshui Road Expressway and Shanghai Yan'an Viaduct. The road sections of the shooting sites do not contain any on/off ramps and are all without significant gradients or curves. During the overall duration of shooting, no accident or vehicle breakdown occurred. The camera was set in a certain roadside building on both occasions. Of all the data collected, 13 696 is from Zhengzhou Jinshui Road Expressway, 7 838 from Shanghai Yan'an Viaduct on sunny days and 12 141 on snowy days (Tables 1–3). Analysis of these data is detailed in Sect. 4.

Table 1 Number of data pairs from Shanghai Yan'an Viaduct (sunny day, rush hour)

h/m	v/(km·h^{-1})										
	< 8	[8,14)	[14,20)	[20,26)	[26,32)	[32,38)	[38,44)	[44,50)	[50,56)	≥ 56	Total
< 15	111	359	623	824	788	532	260	110	44	22	3 673
[15,20)	7	39	155	304	495	507	326	214	88	47	2 182
[20,30)	4	15	49	136	257	343	262	215	142	94	1 517
[30,50)	0	1	5	18	45	86	78	67	71	61	432
≥ 50	0	0	1	1	2	1	5	9	8	7	34
Total	122	414	833	1 283	1 587	1 469	931	615	353	231	7 838

h — headway distance, v — velocity

Table 2 Number of data pairs from Zhengzhou Jinshui Road Expressway

h/m	v/(km·h^{-1})										
	< 8	[8,14)	[14,20)	[20,26)	[26,32)	[32,38)	[38,44)	[44,50)	[50,56)	≥ 56	Total
< 15	17	37	120	206	177	135	56	17	12	4	781
[15,20)	36	46	161	319	376	317	196	74	21	7	1 553
[20,30)	58	69	293	670	834	775	521	266	133	41	3 660
[30,50)	66	84	239	606	868	869	707	471	173	112	4 195
≥ 50	96	60	168	405	698	723	603	389	219	146	3 507
Total	273	296	981	2 206	2 953	2 819	2 083	1 217	558	310	13 696

h — headway distance, v — velocity

Table 3 Number of data pairs from Shanghai Yan'an Viaduct (snowy day)

h/m	v/(km·h^{-1})										
	< 8	[8,14)	[14,20)	[20,26)	[26,32)	[32,38)	[38,44)	[44,50)	[50,56)	≥ 56	Total
< 15	15	23	73	306	742	869	435	152	56	110	2 781
[15,20)	32	37	54	260	809	1 182	846	333	100	122	3 775
[20,30)	44	43	56	203	673	1 145	1 061	530	176	159	4 090
[30,50)	23	13	21	69	173	317	358	259	127	68	1 428
≥ 50	3	2	1	4	13	14	17	8	3	2	67
Total	117	118	205	842	2 410	3 527	2 717	1 282	462	461	12 141

h — headway distance, v — velocity

Moreover, because the reciprocal of headway distance makes vehicle density, which is defined as the number of vehicles per unit distance, and the product of vehicle density and vehicle velocity is vehicle flow, velocity-headway distance data pairs can be easily transformed into velocity-density data pairs and flow-density data pairs for further studies. Still we need to point out that to guarantee accuracy, the measuring of vehicle flow takes much more time than that of velocity and density. Therefore, velocity-density and flow-density data pairs obtained by common detectors are not simultaneous in a strict manner. However, the method in this paper is able to overcome such a shortcoming.

4 Data analysis

4.1 Distribution of mean velocity

The collected samples of data pairs are shown in Tables 1–3, where all the data are divided into 10 intervals in the range of velocity and 5 intervals in the range of headway distance. As it is shown that, with the change of velocity, each row has a zenith which indicates the most number of samples in a certain headway distance interval. Considering the fact that the number of samples on either side of the zenith decreases monotonously, the distribution of velocity in each row can be approximated as normal distribution (Jarque-Bera tests have also been conducted on the data in Tables 1–3. Results of the hypothesis show that the samples can not be rejected at the significance level of 5%. Therefore, the assumption of normal distribution is reasonable). Therefore, mean velocity is used to represent the overall characteristics of the velocity in the interval of headway distance. Table 4 shows that the mean velocity becomes higher with the increase of headway distance (with only one exception). Weighted mean velocity manifests the same tendency in the last row. All this reflects a basic law of traffic flow that the mean velocity becomes higher when there are fewer vehicles on the road.

Table 4 Mean velocity categorized by headway distance (km/h)

	h/m					
	< 15	[15,20)	[20,30)	[30,50)	≥ 50	Total
SH (sunny)	25.87	33.48	37.97	43.26	48.19	31.39
Zhengzhou	52.83	54.66	56.57	58.35	59.09	57.33
SH (snowy)	34.61	36.10	37.83	39.44	35.30	36.73
Wtd. mean	32.14	39.18	45.25	52.81	58.55	43.87

h — headway distance

In Table 5, the 5 intervals of headway distance are further divided into 19 equal intervals after being normalized (the normalized density is defined as ρ/ρ_j, where ρ_j stands for congestion density, approximately 143 veh/km). Based on Table 5, Fig. 3 is drawn showing that mean velocity on Shanghai Yan'an Viaduct on sunny days and Zhengzhou Jinshui Road Expressway drops in different degrees and the difference is enlarged when the normalized density increases. As far as those sets of samples whose number exceeds 50

Table 5 Mean velocity and number of data pairs categorized by headway distance

h/m	ρ/ρ_j	Shanghai, sunny		Zhengzhou		Shanghai, snowy	
		N_s	V_m/(km·h^{-1})	N_s	V_m/(km·h^{-1})	N_s	V_m/(km·h^{-1})
> 93.33	[0,0.075)	0	N/A	304	57.65	0	N/A
(56,93.33]	[0.075,0.125)	17	45.44	2 391	59.10	32	33.80
(40,56]	[0.125,0.175)	92	48.23	2 502	58.94	258	39.52
(31.11,40]	[0.175,0.225)	271	42.86	2 173	58.30	978	39.55
(25.45,31.11]	[0.225,0.275)	512	40.61	1 963	57.14	1 459	38.30
(21.54,25.45]	[0.275,0.325)	674	37.50	1 473	56.43	1 866	37.99
(18.67,21.54]	[0.325,0.375)	886	35.86	1 015	55.23	1 922	36.75
(16.47,18.67]	[0.375,0.425)	913	33.83	701	54.75	1 678	36.02
(14.74,16.47]	[0.425,0.475)	937	31.74	461	54.31	1 369	35.89
(13.33,14.74]	[0.475,0.525)	867	29.99	307	53.02	1 031	35.30
(12.17,13.33]	[0.525,0.575)	738	27.98	178	52.06	636	34.40
(11.20,12.17]	[0.575,0.625)	633	26.19	105	51.73	376	34.85
(10.37,11.20]	[0.625,0.675)	429	24.55	55	53.53	216	34.55
(9.66,10.37]	[0.675,0.725)	332	22.70	23	52.58	131	33.07
(9.03,9.66]	[0.725,0.775)	185	21.25	18	52.16	80	32.70
(8.48,9.03]	[0.775,0.825)	148	17.80	7	61.29	49	29.72
(8,8.48]	[0.825,0.875)	78	15.96	8	55.54	26	29.04
(7.57,8]	[0.875,0.925)	72	13.66	3	49.30	13	31.44
≤ 7.57	[0.925,1]	54	11.60	9	49.72	21	27.18
Total		7 838	31.39	13 696	57.33	12 141	36.73

h — headway distance, N_s — number of samples, V_m — mean velocity are considered, the mean velocity on Zhengzhou Jinshui Road Expressway is always higher than that on Shanghai Yan'an Viaduct on sunny days when the normalized density increases from 0.125 to 0.675 (18 veh/km to 97 veh/km). This is due to the fact that the overall traffic condition on Zhengzhou Jinshui Road Expressway is much better than that on Shanghai Yan'an Viaduct. The latter suffers heavy traffic every now and then. However, on Zhengzhou Jinshui Road Expressway, vehicles usually remain at relatively high velocity even if the overall density is high.

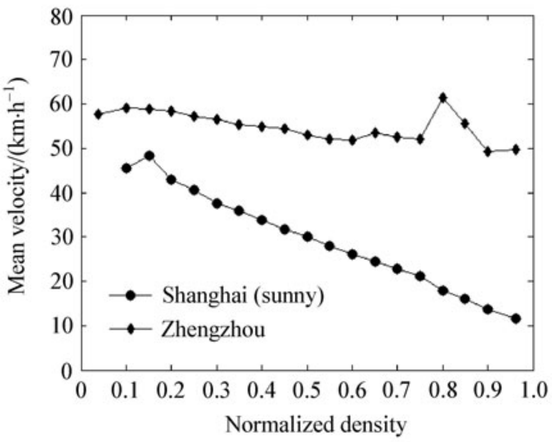

Fig. 3 Comparison of mean velocity between Shanghai (sunny days) and Zhengzhou

4.2 Relations between climate and traffic

The climate also has a crucial impact on traffic flow [11]. When the headway distance is short (e.g., less than 15 m), the mean velocity on Shanghai Yan'an Viaduct on sunny days (note that it is rush hour on a weekday morning) is 25% lower than that in the same location on a snowy-day afternoon, but when the headway distance is long (e.g., more than 50 m), the mean velocity on Shanghai Yan'an Viaduct on sunny days is 36% higher than that in the same location on snowy days. All this suggests that real road traffic is so complex [12] that many factors such as location and climate need to be taken into consideration during the formation of traffic flow models. However, snow does not necessarily induce less headway distance—the number of vehicles with headway distance less than 30 m accounts for 88% of the total on snowy days, which is very close to that on sunny days.

It is shown in Fig. 4 (drawn based on Table 5) that the mean velocity on sunny days is higher than that on snowy days when the normalized density is less than 0.3. However, when the normalized density is more than 0.3, the mean velocity on sunny days becomes lower than that on snowy days and the difference continues to magnify. The reason for this phenomenon that the mean velocity on snowy days has minor fluctuation is (1) under low density, drivers prefer to keep a low velocity considering the fact that the road surface might be slippery because of snow; (2) under high density, drivers barely change lanes so as not to hinder the overall continuity of traffic flow in bad weather.

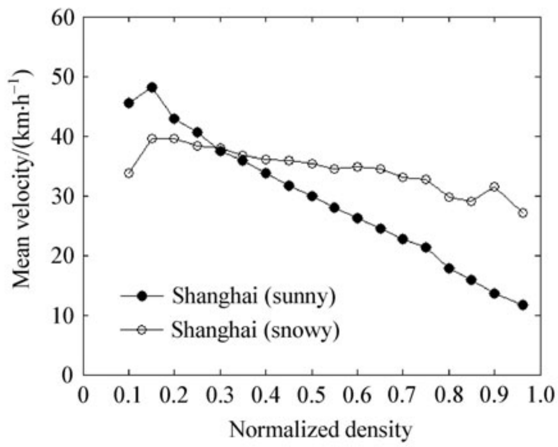

Fig. 4 Mean velocity comparison between sunny days and snowy days in Shanghai

At present there are two major directions of research on the relations between climate and traffic: (1) comparing traffic flow data obtained on workdays with that on weekends; (2) investigating the effect of climate change or weather forecast on drivers' behaviors [13–15]. As it is shown in Table 4, the change of traffic flow parameters on snowy days has a similar trend to that on sunny days. This may mean that only the coefficients need to be adjusted for traffic flow models to describe snowy-day traffic.

4.3 Aggressive and careful drivers

Particularly among the data obtained from Zhengzhou Jinshui Road Expressway, the mean velocity is still 52.83 km/h while the headway distance is shorter than 15 m. According to conventional traffic flow models, vehicles will never reach that level of velocity when the density is that high. However, in the sample of 13 696 data pairs, 574 data pairs reach 48 km/h or higher while the headway distance is shorter than 15 m. Actually it can often be observed in real road traffic that a group of vehicles with very short headway distance move at fairly a high speed. Such phenomenon may add to the non-linear characteristics of low-density traffic.

Velocity-headway distance data pairs have the advantage of being related closely to cellular automaton traffic flow models. The data pairs can provide basic information to many crucial issues of cellular automaton modeling, such as determining the proportions of different driving behaviors in real road traffic. In the research of cellular automaton traffic flow models, Wu [16,17] categorized drivers into two typical types—aggressive drivers and careful drivers—by their driving characteristics. Aggressive drivers are prone to overtake and change lanes. In this paper two different CA traffic flow models are used to describe the behavior of these two types of drivers.

As to how to distinguish these two types of drivers, the following attempt is made—those drivers driving at 35 km/h and higher with the headway distance shorter than 15 m as well as those at 45 km/h and higher with the headway distance shorter than 20 m are grouped into aggressive drivers, and all the rest are grouped into careful drivers. In this case, v/h is tentatively used to measure the behavior of drivers, where the unit of v (velocity) is km/h and that of h (headway distance) is m. Drivers are defined as aggressive drivers if $v/h > 2.3$, while all the rest are defined as careful drivers. By such standard, the proportion of aggressive drivers is about 30% in the sample of Zhengzhou Jinshui Road Expressway, while that on Shanghai Yan'an Viaduct on sunny days and snowy days is 28% and 27%, respectively. The difference is interfered by both traffic conditions and climate. For illustration, all the data pairs collected on three occasions are divided evenly into 200 groups as per density. Each group is rearranged as per velocity and the mean velocity of every 10 successive data is calculated. The result is shown in Fig. 5 after the data are transformed into density (veh/km) and flow (veh/h). The horizontal line is where $v/h = 2.3$ (i.e., flow = 2 300 veh/h). The dots above the line represent the data suggesting aggressive driving behaviors, and all the rest represent the data suggesting careful driving behaviors. The fact that the samples on Zhengzhou Jinshui Road Expressway (Fig. 5c) have the largest number of aggressive drivers is assumed to be influenced by their particular traffic condition, because their flow rate is higher than that on Shanghai Yan'an Viaduct (Figs. 5a and 5b).

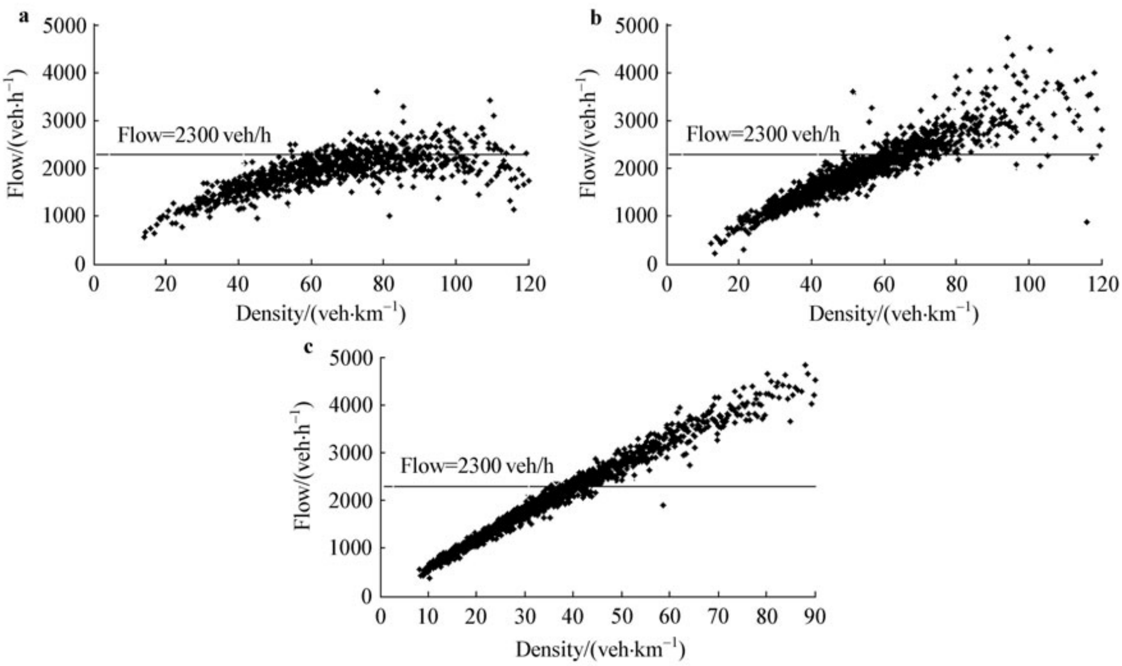

Fig. 5 Distinguishing standard of two different types of drivers: **a** Shanghai (sunny); **b** Shanghai (snowy); **c** Zhengzhou

5 Summary and expectation

A video-based measurement is proposed to collect traffic flow data on urban expressways. This measurement is able to collect various traffic flow data from traffic videos efficiently and establish close relations between traffic videos and traffic flow models. The input of the system consists of image sequences taken from traffic videos and the output is velocity-headway distance data pairs which are genuinely simultaneous and can be further converted into velocity-density and flow-density data pairs. Over 33 000 data pairs have been collected including those on snowy days. The results indicate that traffic flow is basically non-linear and comprises many factors such as location and climate. Mean velocity and headway distance in the three sets of samples are used to study these factors. Furthermore, a tentative standard distinguishing aggressive and careful drivers is presented, which may establish relations between the data pairs and cellular automaton traffic flow models. In addition, compared with most traffic flow measurements, the source material required by this method can be obtained very easily, which shows that traffic control and prediction are possible to achieve with low-cost hardware.

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