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An Investigation on Vehicle's Fuel consumption and Exhaust Emissions in Different Driving Conditions

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ABSTRACT: In this paper, vehicle's fuel consumption and exhaust emissions are investigated in different driving conditions based on driving segments clustering. Driving data collection is performed using global positioning systems in real traffic conditions. The driving data is clustered into five groups using k-means clustering technique. Vehicle's fuel consumption and exhaust emissions (i.e. HC, NOx and CO) are investigated in different driving conditions using computer simulations. The relationship between driving features and vehicle's fuel consumption and exhaust emissions is also presented. According to the simulation results, vehicle's fuel consumption decreases as average velocity increases from very congested traffic condition to freeway traffic condition. The most HC is produced is low speeds. The results also demonstrate that high accelerations and decelerations cause high amount of NOx. About the CO emission, a moderate driving in which the velocity and accelerations are not very high or very low, leads to the least amount of CO.

Key words: Vehicle, Fuel consumption, Exhaust emission, Driving pattern,K-means clustering, Traffic condition

INTRODUCTION

Traffic flow in each city or region contains different driving conditions which take place repeatedly. The driving condition varies from place to place or from public transportation such as buses to private vehicles. The driving conditions are identified by their features. The driving features have been investigated in previous studies (Ericsson, 2000 and 2001).

Traffic flow modeling and driving condition analysis have many applications in various areas such as intelligent transportation, adaptive cruise control, pollutant emissions dispersion and safety. A group of the studies in this area are related to mathematical modeling of the traffic flow (Nagel *et al.*, 2003; Kerner, 2004; Kerner *et al.*, 2007; Chiou *et al.*, 2009; Goswami, 2009). In another group of studies, driving pattern recognition is utilized in order to improve driving safety (Lee *et al.*, 2006; Langford and Koppel, 2006). In some other researches, the pollutant emissions dispersion in the air (Dirks *et al.*, 2003; Chan and Ning, 2005; Rehman *et al.*, 2009; Halek *et al.*, 2010) and driving cycle development (Montazeri-Gh and Naghizadeh, 2007; Kamble *et al.*, 2009) have been investigated.

Beside the above mentioned applications, the use of traffic information in intelligent hybrid electric vehicle (HEV) power management systems has become one of the most important applications in the area of driving conditions analysis, which has attracted a lot of interest recently among the researchers (Lin *et al.*, 2004; Langari and Won, 2005; Montazeri-Gh *et al.*, 2008; Chen *et al.*, 2006).

In this paper, vehicle's fuel consumption and exhaust emissions in different driving condition are investigated. For this purpose, at first driving data gathering is performed in real traffic condition. The driving data is then clustered into five groups. A scientific approach is conducted for the clustering using k-means algorithm and two driving features including average velocity and variance of velocity.

The structure of this paper is as follows. Section 2 is allocated to driving data gathering using global positioning systems and data segmentation. Driving features, k-means clustering technique and driving patterns clustering are presented in section 3. Then in section 4, five traffic conditions are defined based on the clustering results and vehicle's fuel consumption and exhaust emissions are studied in different traffic conditions.

MATERIALS & METHODS

In this study, driving data collection is performed in real traffic conditions in order to provide an actual database of driving patterns. Data gathering is done

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in the city of Tehran using Advanced Vehicle Locating (AVL) devices installed on private cars. The AVL device operates based on Global Positioning System (GPS). The AVL device which is used in this study is shown in Fig. 1. The driving data includes date/time, number of the satellites, longitude, latitude, speed and altitude of vehicle in every second. Fig. 2 presents the path in which driving data is collected in the city of Tehran.

In this study, a "driving pattern" is defined as a 150-sec segment of velocity profile. Four sample driving patterns are shown in Fig. 3 in a velocity profile vs. time. This partitioning is done for extraction of driving features and driving data analysis.

Two driving features including average velocity and variance of velocity are calculated for driving patterns. The average velocity (V_{ave}) is formulated as follows.

$$V_{ave} = \frac{1}{n}\sum_{i=1}^{n} v_i \qquad (1)$$

where n is length of driving patterns and v_i is velocity value in the i^{th} second. Variance of velocity (σ_v) is also defined as below.

$$\sigma_v = \frac{1}{n}\sum_{i=1}^{n} (v_i - V_{ave})^2 \qquad (2)$$

Fig. 1. The AVL device

Fig. 2. Path in which driving data is collected in the city of Tehran

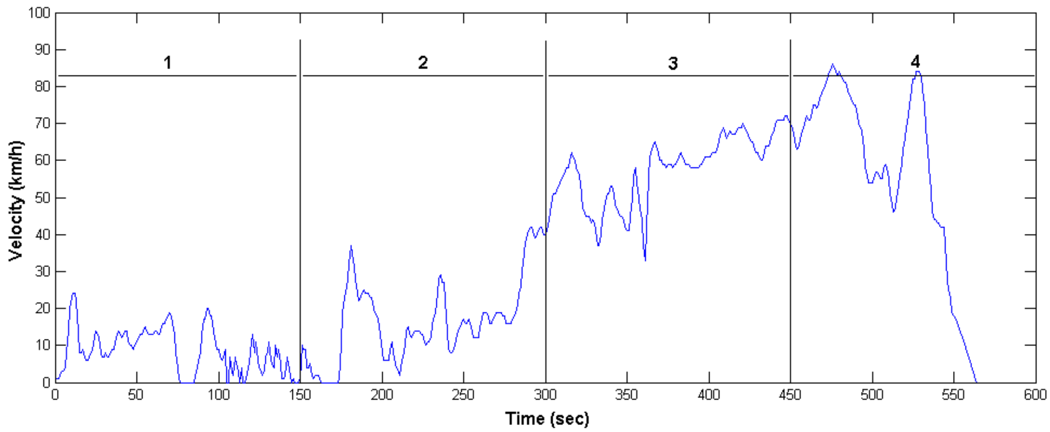

Fig. 3. Four sample driving patterns

In order to clear the distribution of driving patterns in driving features space, a scatter plot is presented in Fig. 4. In this figure, each driving pattern is plotted as a point in 2-dimensional feature space. As demonstrated in the figure, driving patterns are very different from each other regarding to their features. Their average velocity varies from zero to 120 km/h and the bound of variance of velocity is from zero to 2500 $(km/h)^2$. In the following, the driving patterns are clustered and difference between them is investigated.

Clustering in N-dimensional Euclidean space R^N is the process of partitioning a given set of n points into a number, say K, of groups (or, clusters) based on some similarity/dissimilarity metric (Maulik and Bandyopadhyay, 2000). Let the set of n points $\{x_1, x_2, \ldots, x_n\}$ be represented by the set S and K clusters be represented by

$$C_1, C_2, \ldots, C_K \quad \text{Then}$$

$$C_i \neq \varnothing \quad for\ i = 1, \ldots, K$$

$$C_i \cap C_j = \varnothing \quad for\ i = 1, \ldots, K,\ j = 1, \ldots, K\ and\ i \neq j$$

and $\bigcup_{i=1}^{K} C_i = S$

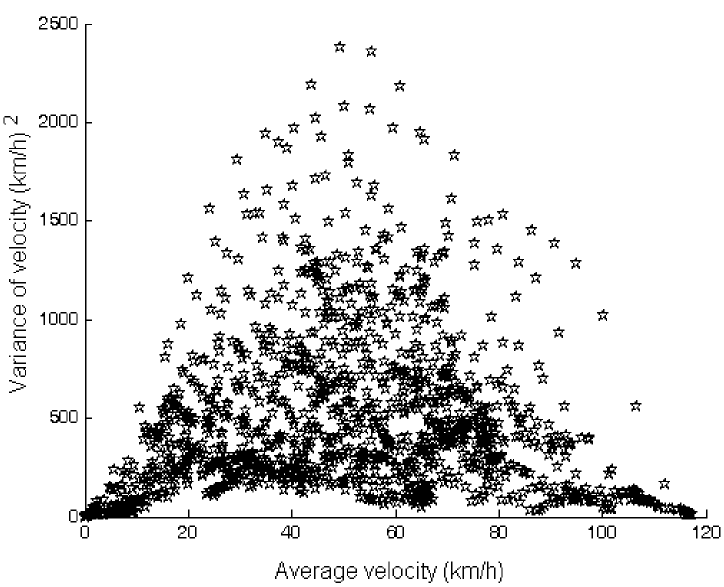

Fig. 4. Scatter plot of driving patterns in feature space

One of the most widely used clustering techniques available in the literature is K-means algorithm (Tou and Gonzalez, 1974). The K-means algorithm attempts to solve the clustering problem by optimizing a given metric. The steps of the K-means algorithm are described here briefly (Maulik and Bandyopadhyay, 2000).

Step 1: Choose K initial cluster centers $z_1, z_2, \ldots, z_K$ randomly from the n points $\{x_1, x_2, \ldots, x_n\}$.

Step 2: Assign point x_i, $i = 1,2,\ldots,n$ to cluster C_j, $j \in \{1,2,\ldots,K\}$ if

$$\left\| x_i - z_j \right\| < \left\| x_i - z_p \right\|,\ p = 1,2,\ldots,K, and\ j \neq p \tag{3}$$

Ties are resolved arbitrarily.

Step 3: Compute new cluster centers $z_1^*, z_2^*, \ldots, z_K^*$ as follows:

$$z_i^* = \frac{1}{n_i} \sum_{x_j \in C_i} x_j, \quad i = 1,2,\ldots,K \tag{4}$$

where n_i is the number of elements belonging to cluster C_i.

Step 4: If $z_i^* = z_i$, $i = 1,2,\ldots,K$ then terminate. Otherwise, continue from step 2.

Note that in case the process does not terminate at Step 4 normally, then it is executed for the maximum number of iterations. In this section, the driving patterns are clustered using k-means algorithm. As mentioned before each driving pattern has two features and can be plotted as a point in 2-dimensional space (Fig. 4). After the clustering the scatter plot of the sample driving data, presented in Fig. 4, is demonstrated in Fig. 5. Each driving pattern cluster has its own characteristics which are analyzed in section 5.

In order to assess the influence of traffic conditions on vehicle's fuel consumption and exhaust emissions, a real vehicle is simulated using ADVISOR software (Markel and Brooker, 2002). Velocity profile is the input of the software and the output is vehicle's fuel consumption and exhaust emissions. Parameters of the vehicle model including engine map, vehicle's weight, role resistance, air resistance and gear box are taken from a common vehicle in Iran called "Samand" with the specifications presented in Table 1.

In addition, in order to assess the effectiveness of the simulations, the simulation results are verified by an experimental test. Fig. 6 demonstrates the experimental setup containing a dynamometer chassis and an exhaust emissions analyzer. Using this setup, the test results are provided for the Samand vehicle on the New European Driving Cycle (NEDC). The NEDC and the velocity profile which is passed by the vehicle are depicted in Fig. 7. Fuel consumption (FC) (L/100 km) and exhaust emissions (gr/km) of the vehicle on NEDC are presented in Table 2. As shown in the table, there is a good agreement between the simulation results and the test results which supports the simulation tool used in this study.

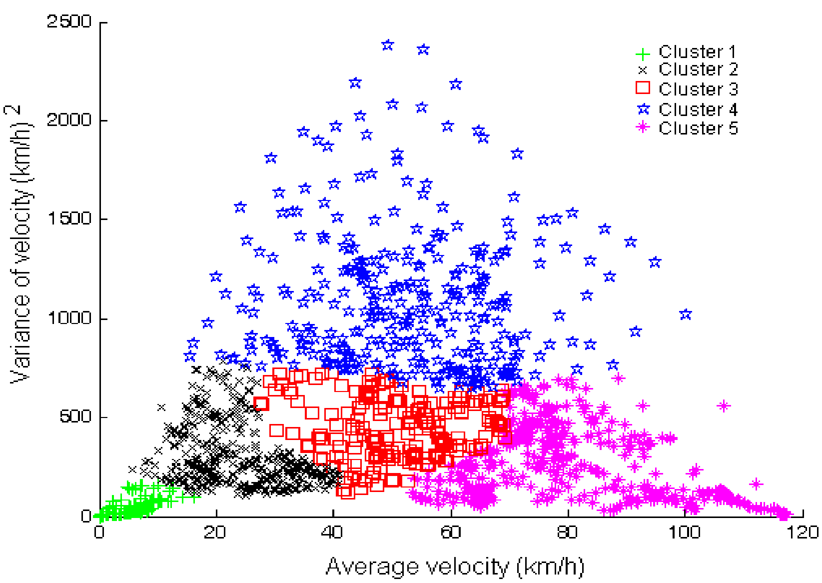

Fig. 5. Clusters of driving patterns in feature space

Table 1. Specifications of Samand vehicle

		Parameter	Value	unit
Vehicle	1	total vehicle mass	1250	kg
	5	vehicle glider mass	905	kg
	6	coefficient of aerodynamic drag	0.318	
	7	frontal area	2.1	m^2
	8	fraction of vehicle weight on front axle	0.6	
	9	height of vehicle center-of-gravity	0.64	m
	10	wheelbase	2.67	m
Combustion Engine	11	peak engine power	82	kw
	12	rotational inertia of the engine	0.18	kg*m^2
	13	total engine/fuel system mass	262	kg
	14	fuel density	0.753	g/l
	15	lower heating value of the fuel	42.5	kJ/g
	16	exterior surface area of engine	0.2626	m^2
	17	air/fuel ratio (stoic) on mass basis	14.5	
	18	engine coolant thermostat set temperature	86	C
	19	average cp of engine	500	J/kgK
	20	average cp of hood & engine compartment	500	J/kgK
	21	surface area of hood/eng compt.	1.5	m^2

Fig. 6. Experimental setup containing a dynamometer chassis and an exhaust emissions analyzer

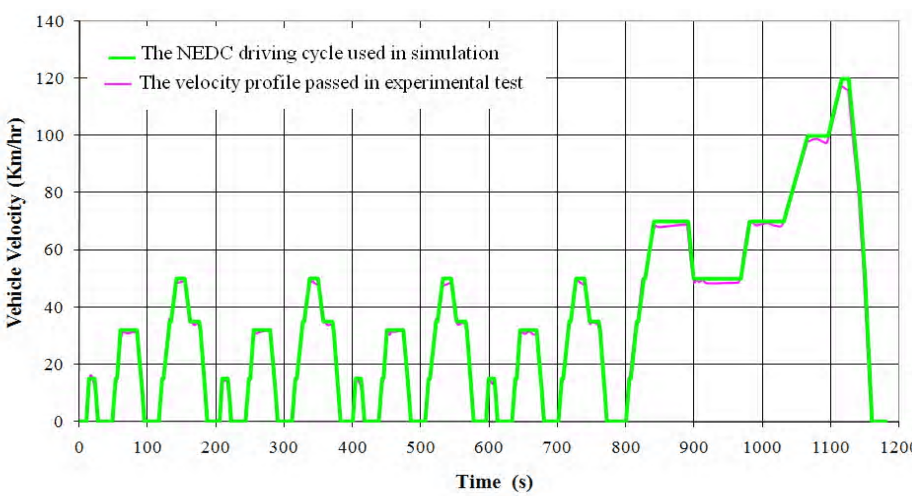

Fig. 7. NEDC and velocity profile which is passed by the vehicle in experimental test

Table 2. experimental test and simulation results on NEDC

	Test Result	Simulation Result	Error (%)
FC (L/100km)	7.917	8.2	3.57
HC (g/km)	0.041	0.042	2.44
Nox (g/km)	0.018	0.019	5.56
CO (g/km)	0.521	0.514	-1.34

RESULTS & DISCUSSION

In the previous sections the driving patterns were defined and clustered based on their features. In this section, we focus on characteristics of each traffic condition and differences between the traffic conditions are discussed. Using the two previously mentioned driving features; the “traffic conditions” are defined in this study. A traffic condition number has been allocated to each driving pattern based on the clustering’s results and regarding to its features. The traffic condition number varies from 1 to 5 regarding to the cluster number allocated to each driving pattern. Beginning the traffic conditions analysis with Fig. 5, the traffic conditions can be described as follows:

1-Very congested traffic condition which is shown with label 1 in Fig. 5. This traffic condition contains very low average velocity and also very low variations in the velocity. In this traffic condition vehicles move with very low velocities without any high acceleration or deceleration.

2-Congested traffic condition which is shown with label 2 in Fig. 5. This traffic condition contains low average velocity and also low variations in the velocity. In this traffic condition vehicles move with low velocities and moderate accelerations or decelerations.

3-Urban traffic condition which is shown with label 3 in Fig. 5. Comparing to the two previous traffic conditions (very congested and congested), this traffic condition has a wider range of average velocity and the velocities are usually a little more. The variation of the velocity is in medium range.

4-Extra urban traffic condition which is shown with label 4 in Fig. 5. Comparing to the urban traffic conditions, this traffic condition has a wider range of variation of the velocity. The velocity values and consequently the average velocity values are high but not very high. The variation of the velocity is the highest among all traffic conditions.

5-Highway traffic condition which is shown with label 5 in Fig. 5. This traffic condition contains high average velocity but low variations in the velocity. In this traffic condition vehicles move with the highest velocities and moderate accelerations or decelerations.

In the following, characteristics of each traffic condition and difference between them are investigated. Fig. 8 demonstrates relationship between the vehicle’s fuel consumption (litre/100km) and the first driving feature (average velocity) for all driving patterns in the 5 traffic conditions. As depicted in the figure, there are differences between the traffic conditions. It is obvious in the figure that the cloud of the driving patterns (each point stands for a driving pattern) move from top to bottom and left to right from the 1st traffic condition (very congested) to the 5th (highway). In other words, the average fuel consumption (litre/100km) of a driving pattern decreases as the average velocity increases from very congested traffic condition to the highway traffic condition.

Fig. 9 depicts the relationship between the vehicle’s fuel consumption (litre/100km) and the other driving feature (variance of velocity) in different traffic conditions. The figure demonstrates that the first traffic condition (very congested) has the least variance of velocity which means low accelerations and decelerations. The widest range of fuel consumption values is observed in the 1st traffic condition and the widest range of variance of velocity values is seen in the 4th traffic condition. The 2nd and 5th traffic conditions are as same as the 1st traffic condition with relatively low accelerating and decelerating but more limited fuel consumption values. The 3rd traffic condition is like to the 4th but more limited variance of velocity values.

The color map of vehicle’s fuel consumption is presented in Fig. 10 in which the effect of both driving features is demonstrated simultaneously. This plot can be compare to Fig. 5 containing the region of each cluster in the feature space. It can be seen that the most fuel consumption occurs in the first cluster (very congested traffic condition) and the fuel consumption decreases moving to right and up directions in the feature space.

Vehicle’s pollutant emissions are also investigated in this study. Three pollutant emissions (CO, HC and NOx) are considered here and a pollution index is defined as follows:

$$\text{Pollution index} = (CO / 1 + HC / 0.1 + NOx / 0.06) / 3 \tag{5}$$

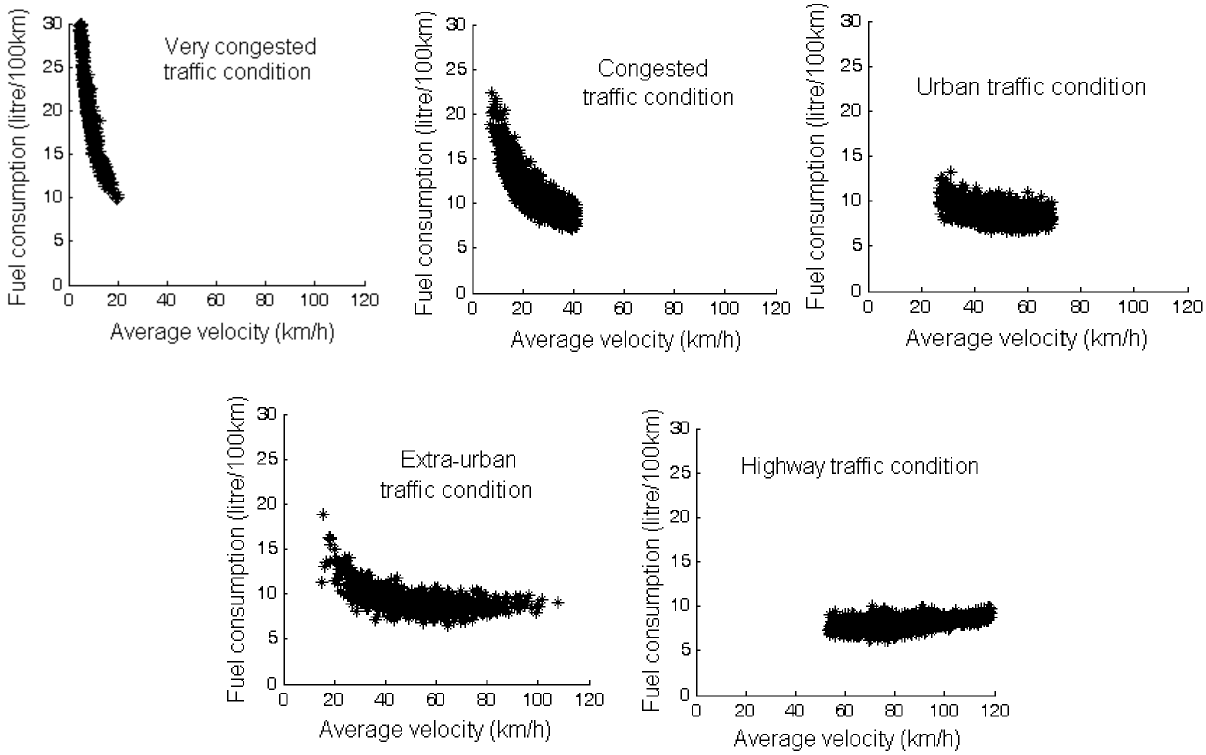

Fig. 8. Fuel consumption vs. average velocity of driving patterns in the 5 traffic conditions

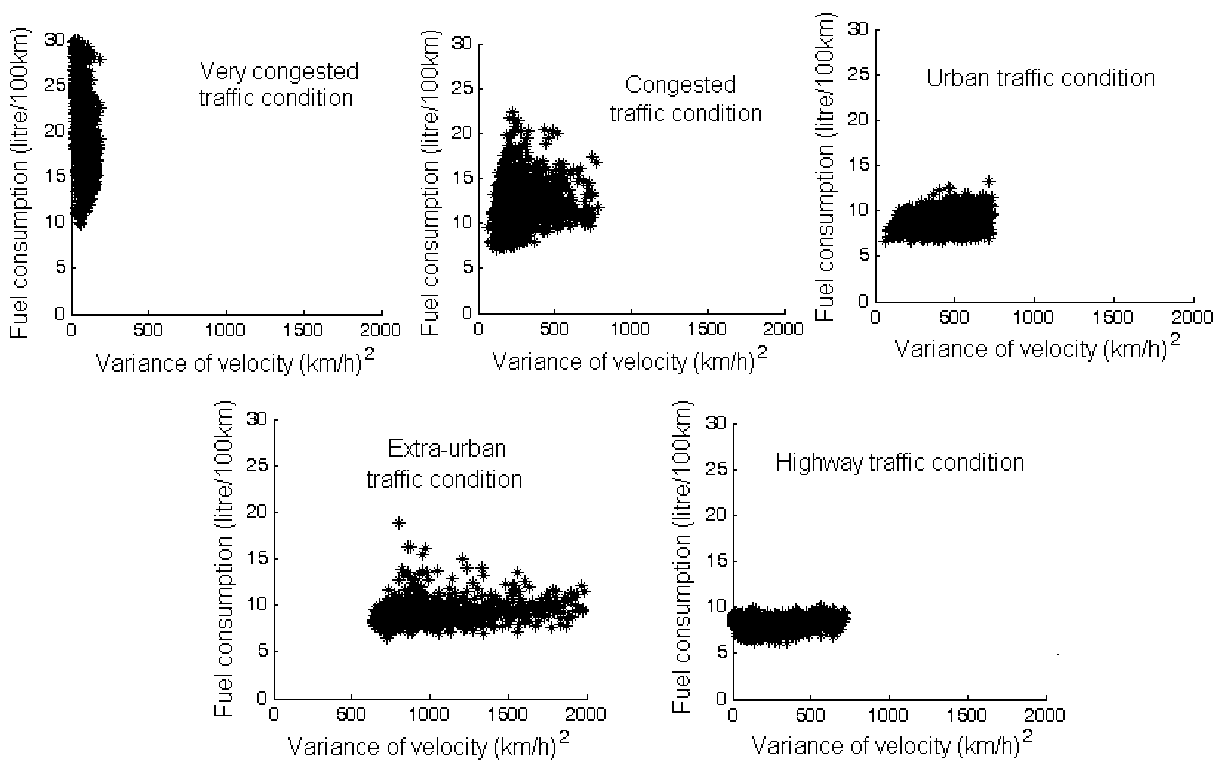

Fig. 9. Fuel consumption vs. variance of velocity of driving patterns in the 5 traffic conditions

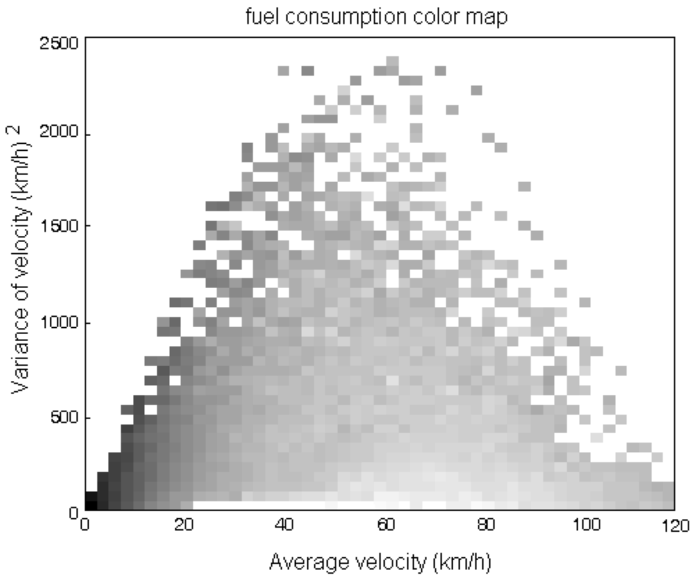

Fig. 10. Color map of fuel consumption vs. the two driving features

In which the average of each pollutant is in gr/km unit. The three constants (1 for CO, 0.1 for HC and 0.06 for NOx) are used for make the pollution index dimensionless. Fig. 11 presents the pollution Index vs. average velocity for all driving patterns in the 5 traffic conditions. It can be seen that like to fuel consumption, the emissions also basically change in different traffic conditions. Color maps of the exhaust emissions are presented in fig s 10 to 12. Comparing to Fig. 5, the following results are achieved. About the HC pollution, the most amount of pollution exists in very congested traffic condition and then in some regions of congested

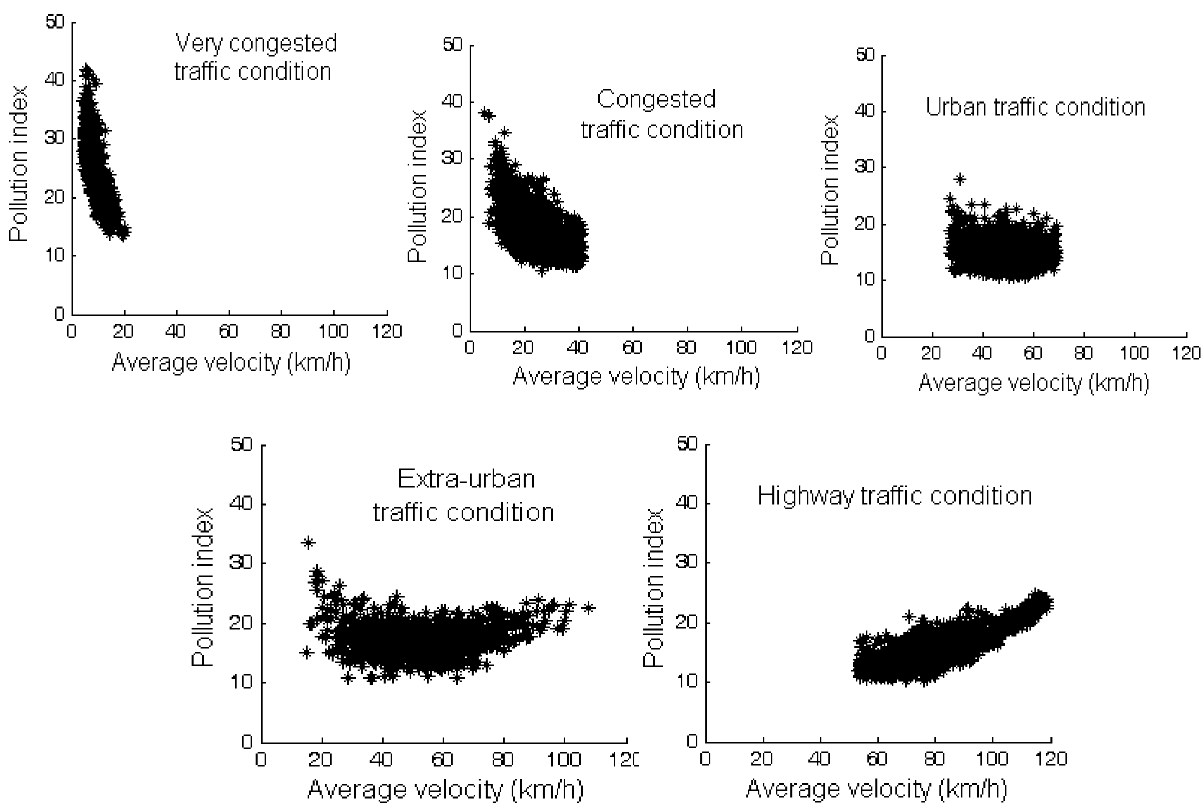

Fig. 11. Pollution Index vs. average velocity of driving patterns in the 5 traffic conditions

and urban traffic conditions. All in all, the HC pollution is produced in the driving patterns with low average velocity (left regions of the plot).

About the NOx pollution, the results are different (Fig. 13). The amount of NOx is high in very congested traffic condition and it decreases moving to right across the average velocity axis but it increases again in highway traffic condition. Altogether the central regions of the plot have the least NOx pollution and the driving patterns with very low or very high average velocity and also the patterns with high acceleration and deceleration cause high amount of NOx.

For the CO pollution, a less regular distribution pattern can be observed in different traffic conditions (Fig. 14). Totally the patterns with a moderate driving in which the velocity and accelerations are not very high or very low, have the least amount of CO pollution.

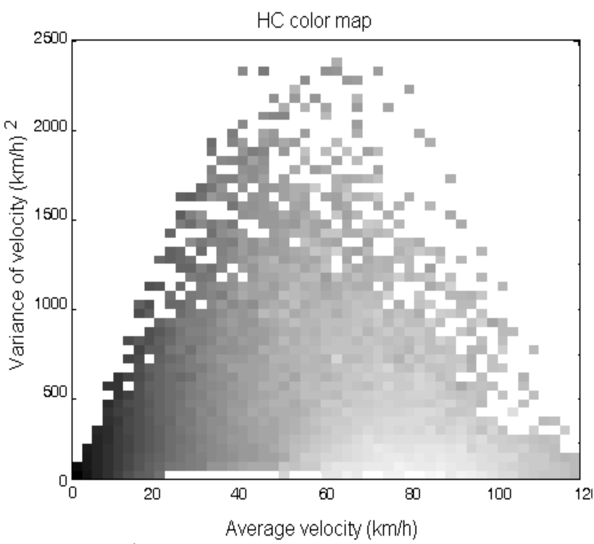

Fig. 12. Color map of HC pollution vs. the two driving features

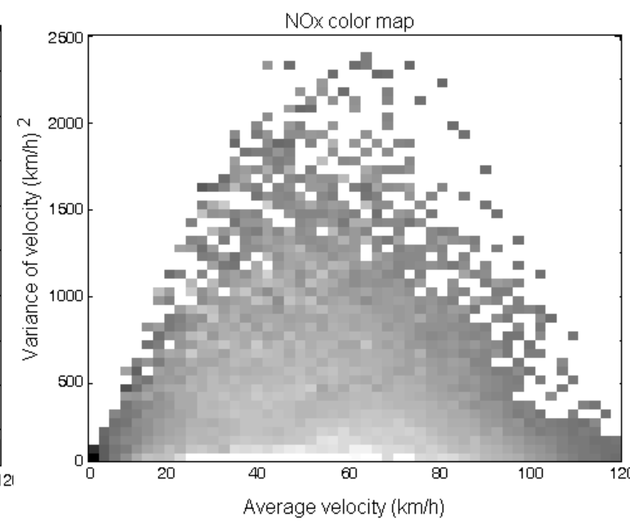

Fig. 13. Color map of NOx pollution vs. the two driving features

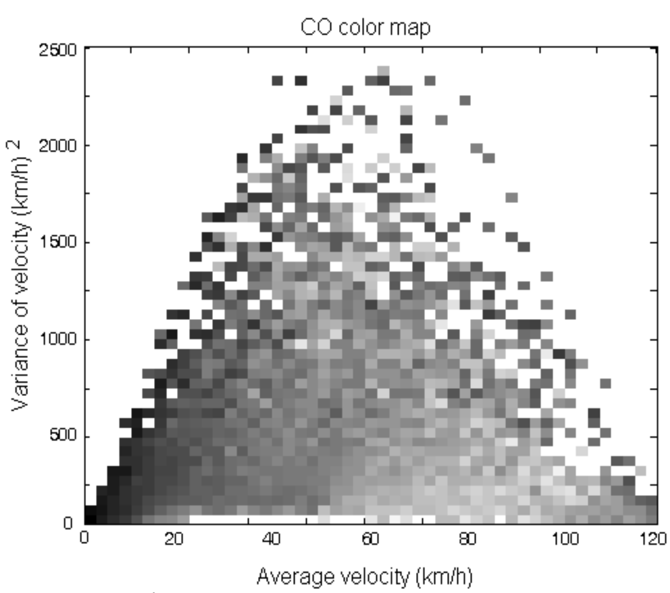

Fig. 14. Color map of CO pollution vs. the two driving features

CONCLUSION

In this study, vehicle's fuel consumption and exhaust emissions have been investigated in various driving conditions. Five traffic conditions including very congested, congested, urban, extra urban and highway, are defined and analyzed based on clustering of driving data. The results demonstrated that there are basic differences between the traffic conditions in viewpoint of vehicle's fuel consumption and exhaust emissions. The results of this study can be used in some areas such as intelligent transportation, pollutant emissions dispersion, driving cycle development and intelligent vehicles.

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