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Driving Behavior Analysis Based on Weighted Cost Function

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ABSTRACT

Driving behaviour analysis is beneficial to road safety and personalized vehicle insurance formulation. Most existing studies describe driving behavior characteristics by constructing various features from driving data. However, drivers' pursuit of the minimum driving cost is the main reason to form different driving behavior characteristics. Therefore, this paper proposes a novel framework that uses the weighted cost function to analyse driving behavior characteristics. Firstly, driving cost function was constructed by the property of comfort, safety, quickness and their weights. Secondly, for each driver, the original driving data was divided into sections according to the definition of six driving manoeuvres. Properties on each driving section were calculated, and then property weights in the driving cost function are calculated by entropy weight method. Finally, according to the obtained property weights, three driving styles are clustered by k-means. Different from the previous studies that can only describe driving behavior characteristics from results, the paper describes driving behavior characteristics from causes. Therefore, the framework proposed in this paper is helpful to deeply understand the differences between different drivers, and beneficial for describing driver decision making.

Keywords: Driving behavior, Cost function, Driving manoeuvre, Property weights

INTRODUCTION

Driving style analysis has become the focus of public attention with the development of technology, which plays a vitally important role in road safety (Guo, et al., 2013; Sagberg, et al., 2015; Kashevnik, et al., 2019), eco-driving (Di Cairano, et al., 2014; Xu, et al., 2020), vehicle insurance (Handel, et al. 2014; Wei, et al., 2016), and intelligent vehicle design (Martinez, et al., 2016; Wang, et al., 2017). Therefore, efficiently recognizing driving styles has been the research focus in recent years.

So far, both subjective and objective methods have been used in previous researches. Generally, subjective methods mostly adopted the questionnaire (Orit, et al., 2004; Ishibashi, et al., 2007). Researchers designed questionnaires according to their experience and asked drivers to fill them out so that they could identify different drivers. In recent years, objective methods have become more and more popular, as they're more objective and easier to implement. For objective methods, most studies constructed statistical features or function features on driving data. These features were used to describe the statistical distributions between various driving behaviors, so those represent diversities of driving behavior characteristics. Using these features, researchers have applied well-trained classifiers such as XGBoost (Shi, et al., 2019), the Markov model (Guardiola, et al., 2014), the Semi-Supervised Tri-CatBoost (Liu, et al., 2020), structural equation models (Zhao, et al., 2019), the semi-supervised support vector (Wang, et al., 2017), and neural networks (Chen, et al., 2021; Chen, et al., 2019) to identify driving styles.

However, the above features just only represent driving behavior from results level, lacking of analysis for causes of driving behavior. As a result, the existed methods are not much help in understanding driving behavior deeply. Beyond that, existed studies may use classifiers to identify driving styles based on labelled data, which acquiring labelled data needs much funding, resources and manpower.

The paper proposes a novel framework for driving style analysis. It uses the weight of cost function to represent driving behavior characteristics and clustering driving styles according to k-means. Considering drivers' decision preferences, the framework constructs features by quantifying the causes of driving behavior. Compared with the previous studies, which only constructed features of driving data, this paper can have a more comprehensive understanding of driving behavior decisions. In addition, different from previous studies, this framework uses k-means to cluster driving styles, which overcomes the disadvantages of manually labelling data.

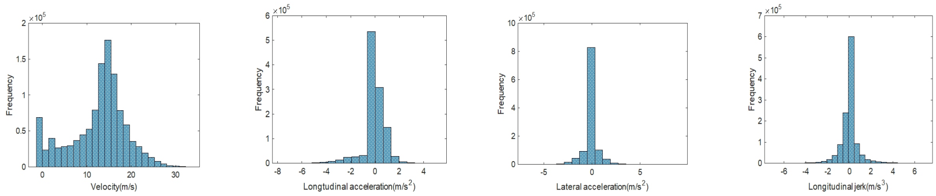
DATA DESCRIPTION

The data set used in this paper is sampled by experiments, which are carried out in the RADS 8 DOF Panoramic Driving Simulation. The test route contains 11 curves and the total round trip is about 10.35 km. 16 drivers (10 males, 6 females; age range 28~50 years old, average age = 29.8, standard deviation (SD) = 2.7; driving experience 0~12 years, average = 7.6 years, SD = 3.3) are paid for their participation in this study, and all drivers are required to drive the vehicle in similar conditions to minimize potential disturbance caused by external factors.

The data recorded by the RADS 8 DOF Panoramic Driving Simulation are recorded at a sampling rate of 60 Hz. Because raw data are volatile, we used a moving-average algorithm to smooth the data. The statistical results from the processed data are shown in Figure 1. The velocity falls in the 0~34 m/s range, longitudinal acceleration falls in the -7 m/s^2~6 m/s^2 range, lateral acceleration ranges from -7 m/s^2 to 9 m/s^2, and longitudinal jerk ranges from -6m/s3~6m/s^3.

METHOD

In driving, the driver takes the driving goal realization as the premise. They comprehensively consider the pursuit of various properties. Drivers make driving decision based on the value of various properties.



(a) velocity (b) longitudinal acceleration (c) lateral acceleration (d) longitudinal jerk

Figure 1: The frequency distribution histograms of processed variables.

Driving Cost Function and Property Weights

Drivers make driving decision based on the value of various properties and on the value of cost function. We choose velocity, longitudinal acceleration, lateral acceleration and jerk to construct the cost function so as to representing drivers' pursuits for comfort, safety and quickness:

$$J = \omega_1 \int_0^T {a_x}^2 \mathrm{dt} + \omega_2 \int_0^T \mathrm{jer}k^2 \mathrm{dt} + \omega_3 \int_0^T {a_y}^2 \mathrm{dt} + \omega_4 \int_0^T (v_d - v)^2 \, \mathrm{dt} \tag{1}$$

Where, T is the duration of the driving manoeuvre; ω_1, ω_2, ω_3, ω_4 are weights for different properties; v_d is the desire velocity, and $v_d = 80km/h$.

The first and the second item in equation (1) represent the pursuit of comfort, the third item represents the pursuit of safety, and the last item represents the pursuit of quickness.

In driving, drivers adjust the weights of each item in equation (1) in order to make the total cost keeps the minimum. Property weight in the cost function describes driver decision-making preference, which is useful for driving style recognition. Therefore, driving behavior features could be described by the property weight, and driving style could be recognized according to those weights.

Road alignment has a salient influence on drivers operation and the cost value. Therefore, sections of driving-straight and turning based on trajectory radius were extracted from the origin driving data. Furthermore, the sections of driving-straight and turning were divided into three types according to vehicle longitudinal acceleration, namely accelerating, driving almost at constant speed and decelerating. Therefore, the original driving data was divided into sections by the six driving manoeuvres, and the manoeuvres are listed in Table 1.

Table 1. The six driving manoeuvres.

Manoeuvres according to road alignment	Manoeuvres according to vehicle longitudinal acceleration		
Driving-straight	accelerating	driving at constant speed	decelerating
Turning	accelerating	driving at constant speed	decelerating

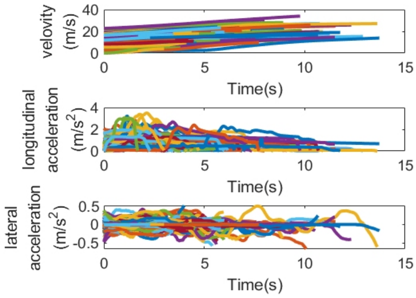
Driving Style Clustering

Weights of the four properties show a driver preference, and the bigger weights imply that the driver prefer the corresponding property. Therefore, the four property weights were used to describe driving characteristics, and k-means was used to cluster different driving style.

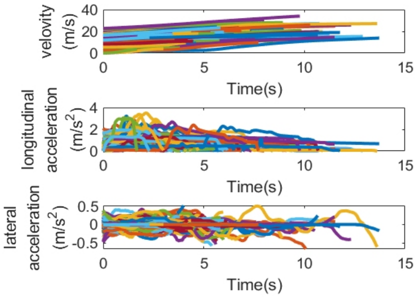
RESULTS AND ANALYSIS

Property Weights

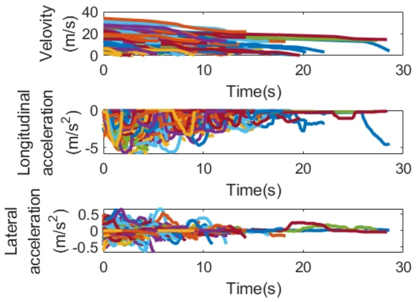
Variable profiles of different driving manoeuvres extracted according to velocity, longitudinal acceleration, and lateral acceleration are shown in Figure 2.



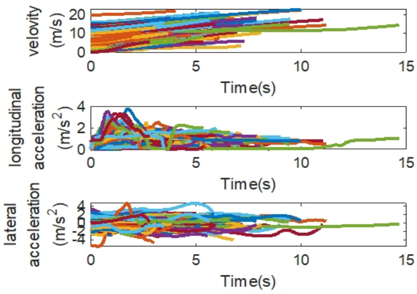
(a) accelerating when driving-straight



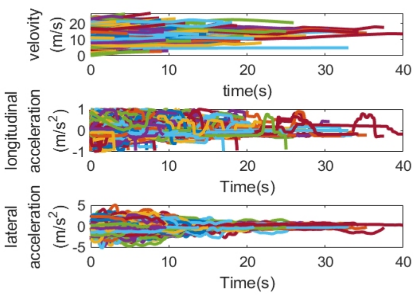
(b) accelerating when turning



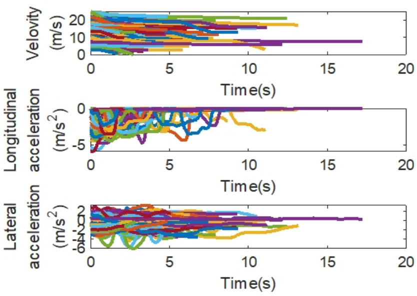
(c) driving at constant speed when driving-straight



(d) driving at constant speed when turning



(e) decelerating when driving-straight



(f) decelerating when turning

Figure 2: Variable profiles of different driving manoeuvres.

It’s obviously that statistical distribution of variables for different driving manoeuvres are distinctly different.

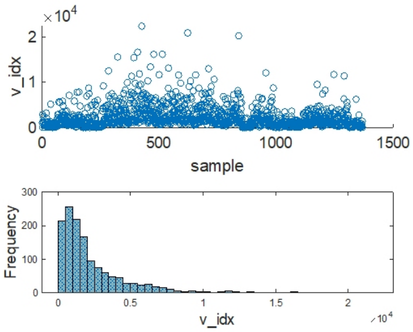
On each driving section, the four items in equation (1) were calculated. Then, property weights were obtained by entropy weight method for each driver.

For one of the participants, the four properties are shown in Figure 3 and Figure 4. Specifically, statistical distribution of lateral acceleration for driving-straight is concentrated, which indicates that there is little difference in safety when driving straight because of the influence of road alignment. In addition, statistical distribution of jerk for turning is more concentrated than driving-straight, and the variability of velocity and longitudinal acceleration has little differences between driving-straight and turning.

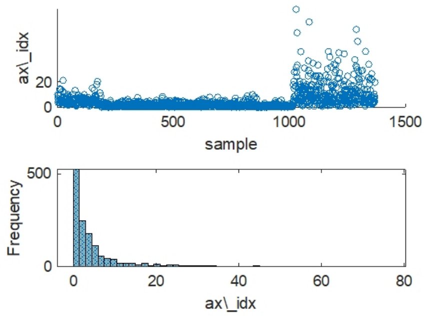
Entropy weight method was used to calculate property weights for every driver (as shown in Figure 5). It’s obvious that the pursuits of quickness among drivers are basically the same. However, the pursuit of comfort and safety varies from person to person. The comfort is often sacrificed when drivers prefer safety, and the quickness is often sacrificed when drivers prefer comfort.

Driving Style

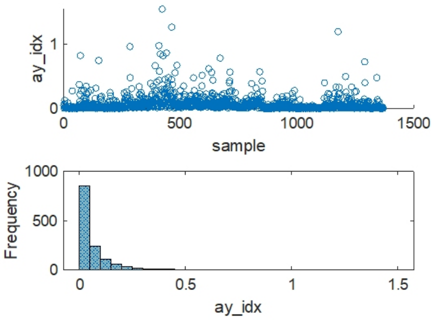
Most studies classify driving style into three clusters: cautious, normal and aggressive. So, we also classified driving style into three clusters. The cluster center of each cluster is shown in Table 2.



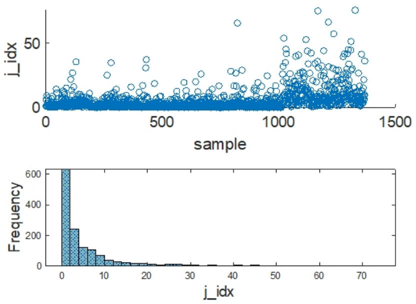
(a) velocity



(b) longitudinal acceleration

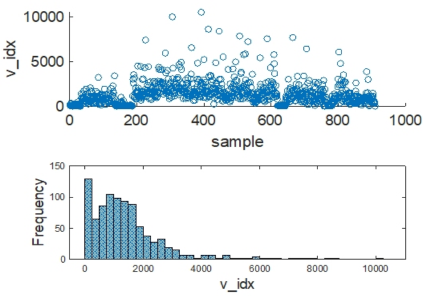


(c) lateral acceleration

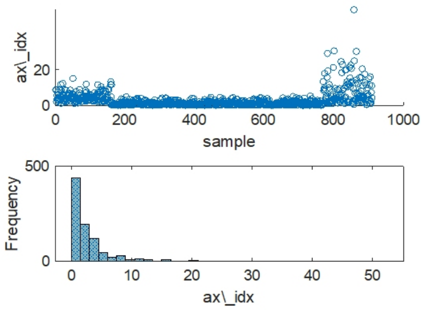


(d) jerk

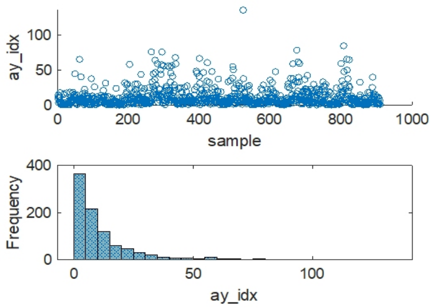
Figure 3: Properties when driving-straight.



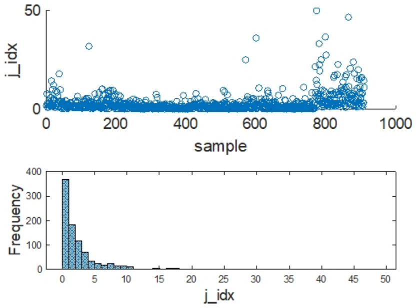
(a) velocity



(b) longitudinal acceleration



(c) lateral acceleration



(d) jerk

Figure 4: Properties when turning.

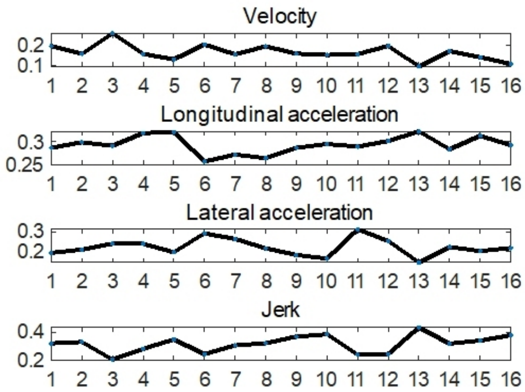


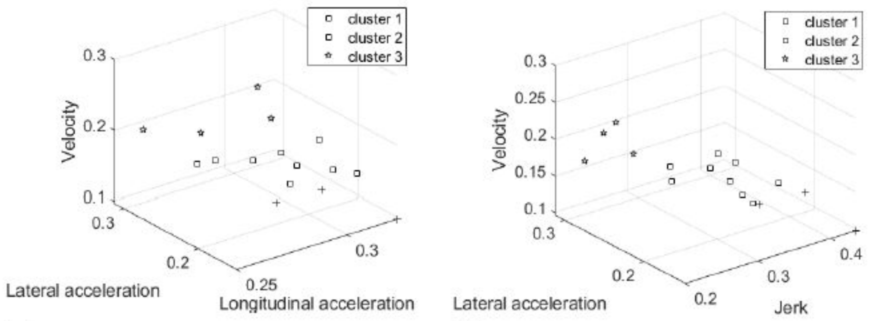
Figure 5: Weights of properties for different drivers.

In Table 2, the ω_1 and ω_2 decrease successively among the three clusters, but ω_3 and ω_4 increase successively. Therefore, we draw conclusion that the cluster1 pay more attention to comfort and less attention to quickness. On the contrary, the cluster 3 prefer quickness than comfort. Therefore, the cluster 1 is cautious, the cluster 3 is aggressive and the cluster 2 is normal.

The details of driving style clustering results in different aspects are shown in Figure 6. The coordinate axes represent property obtained by different variables, and points represent samples. In different perspectives,

Table 2. Cluster center of driving style clusters.

Driving style clusters	Weights of properties			
	ω_1	ω_2	ω_3	ω_4
Cluster 1	0.30	0.40	0.18	0.12
Cluster 2	0.29	0.34	0.20	0.16
Cluster 3	0.28	0.24	0.29	0.19



(a) aspect 1 (b) aspect2

Figure 6: Clustering results of driving style in different aspect.

property weights can be used to describe driving behavior characteristics and effectively recognize various driving style.

CONCLUSION

This paper proposed a novel framework to describe driving behavior characteristics based on weighted driving cost function. Property weights were used to describe driving behaviour characteristics, and driving styles were clustered according to property weights in the cost function of each driver. We evaluated the effectiveness of this framework on real driving data. The results implied that the proposed framework could effectively distinguish different driving styles, and explain the causes of different driving behaviors.

However, there still are some limitations in this paper. The types of driving manoeuvres are simple and subjective in this paper, so that, the data mining method will be applied to obtain more complex and subjective driving manoeuvres. In addition, how to further analyse driving styles using the nonlinear features about the property weights will be explored in the future work.

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