

# CLASSIFICATION OF LONGITUDINAL DRIVING BEHAVIOUR BASED ON SIMULATOR STUDY

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## ABSTRACT

Driving behaviour is a crucial issue for the design and evaluation of in-vehicle driving assistance systems for improving traffic safety, energy efficiency and traffic harmonisation. To improve insight into longitudinal driving behaviour, a simulator study has been set up for analysing and classifying driving behaviour. Two scenarios of lead vehicle performance are designed based on previous research by using an instrumented vehicle and advanced data analysis tools. Twenty-four test drivers participated in the simulator study. The host vehicle state data that indicate the longitudinal driving behaviour of the test drivers (including during the emergency situation), were recorded and comprehensively analysed. The individual diversity of the drivers is investigated based on dissimilarities of the longitudinal driving behaviour. In this research, a K-means clustering algorithm is used, and by using measurable safety parameters, the four main determinants of longitudinal driving behaviour is classified as prudence (aggressive vs. prudent); stability (unstable vs. stable); safety-mindedness (risk prone vs. safety prone); and skilfulness (non-skilful vs. skilful).

## 1. INTRODUCTION

With the economic booming in P.R. China, the number of vehicles has been increasing more than 17% per year since 2005 [Dong, 2008]. The side-effects of this expeditious development are a high rate of traffic accidents (e.g. fatality in 2008 is 73,484) [MPS-DTM, 2008], and increases in emissions (e.g. around 250 million ton CO<sub>2</sub> from vehicles) and congestion costs (e.g. that take around 12.5% income in Beijing) [Foton Index, 2008]. The Chinese authorities have taken various measures to improve traffic safety, environmental impact and network efficiency, through legislation, regulation, education and road infrastructure (re)design. In addition, ITS (Intelligent Transport Systems) is developing rapidly in P.R. China [Wang, et al., 2003; Yang & Hu, 2001]. As part of ITS, in-vehicle driving assistance systems are expected to be implemented for enhancing traffic safety, energy efficiency and traffic harmonisation. For the functional design and evaluation of in-vehicle systems, knowledge and understanding of driver behaviour is an essential prerequisite. This study focuses on the longitudinal driving behaviour of Chinese drivers for the R&D (research and development) of in-vehicle systems.

Longitudinal driving behaviour has been extensively studied from different perspectives, such as psychology (see e.g. [Boer, 1999; Brackstone, et al., 2009]), ergonomics (see e.g. [Van Winsum & Heino, 1996; Van Winsum, 1999; Brackstone, 2000]), physics and traffic engineering (see e.g. [Bexelius, 1968; Gipps, 1981; Kerner & Klenov, 2004; Treiber, et al., 2006; Ossen, 2008]). In the behavioural studies of in-vehicle systems, drivers are, in general, classified by gender, age and driving experience (in terms of years of driving), and the difference of driving behaviour between different driver groups are studied (see e.g. [Hoedemaeker, 1999]). In our previous research, the hypotheses about the differences between different driver groups were tested by using an instrumented vehicle and advanced data analysis tools [Zhang, et al. 2007]. From the analysis of the real world data we do not find statistically significant differences between genders, between

ages, and between number of years of driving experience [Wang, et al. 2010]. In addition, due to the complicated nature of human beings, the information of age, gender and driving experience could not provide abundant foundation to establish a reasonable method to determine driving style and driver characteristics. In this paper, a sophisticated research approach is presented, using simulator study (see e.g. [Kaptein, et al., 1996]) to further explore longitudinal driving behaviour. The main reasons for using driving simulation in this research are: (1) to investigate driving behaviour in potentially dangerous situations, during which emergency braking should be carried out; and (2) to implement optimal experimental control. The research questions are defined as follows:

- How to determine the dissimilarity of the longitudinal driving behaviour, e.g. driving styles and characteristics?
- How to classify the dissimilarity of the longitudinal driving behaviour that will be useful for the design and the evaluation of in-vehicle driving assistance systems?

In the following sections, details of the research method, simulator study design and research results are presented. In addition, the results are discussed and conclusions are drawn.

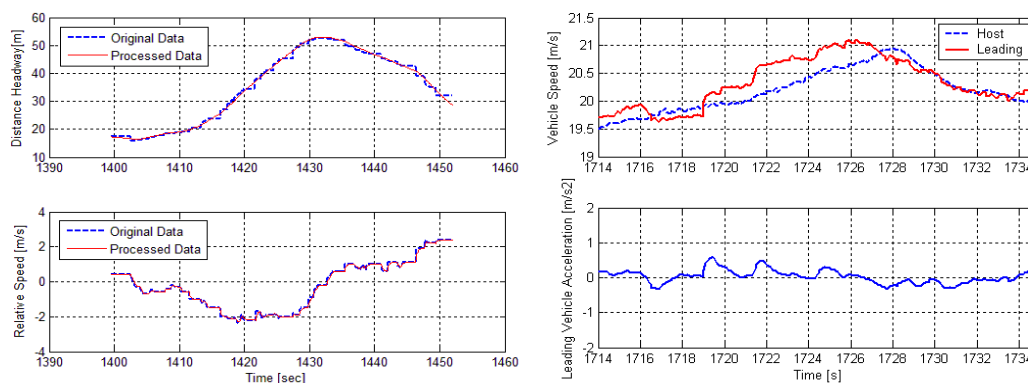
## 2. RESEARCH APPROACH

### 2.1. Lead vehicle state and scenarios

#### 2.1.1. Lead vehicle state analysis

The design of the simulator study of longitudinal driving behaviour is based on the analysis of collected real world data. We have used our developed experimental platform (including an instrumented vehicle and advanced data analysis tools) to study longitudinal driving behaviour in Beijing [Zhang, et al., 2007]. Historical data of forty-five drivers have been post processed and the vehicle movement characteristics have been analysed.

Because only the host vehicle data were recorded during the real world experiments, the lead vehicle states need to be calculated and estimated from the host vehicle state and laser radar data. Car-following data segments were extracted based on the following principles: (1) the distance value difference between the adjacent data points should be less than 4 m; (2) the radar data should not stagnate for more than 3 seconds; (3) the length of the data segment should be more than 20 seconds. A total of 398 data segments were extracted, with a total length of 10894 seconds. The Kalman filter method was used to eliminate noise from the radar data, as well as to estimate the lead vehicle acceleration. The results are shown in Figure 1.



(a) Filter result of distance and relative speed measured by laser radar (b) Estimated lead vehicle speed and acceleration

Figure 1 - Results of using Kalman filter in the real world data post-processing

The results of the analysis of the lead vehicle state are as follows: mean value of the lead vehicle

speed is 18.35 m/s (S.D. = 2.88); the maximal value of the lead vehicle speed is 25.49 m/s, and the minimal value of the lead vehicle speed is 3.28 m/s; the mean value of the lead vehicle acceleration is  $-7.89 \times 10^{-4} \text{ m/s}^2$  (S.D. = 0.38); the maximal value of the lead vehicle acceleration is  $5.11 \text{ m/s}^2$ , and minimal value of the lead vehicle acceleration is  $-7.30 \text{ m/s}^2$ .

The distributions of lead vehicle speed and acceleration values, and the contour diagram of the two variables are presented in Figure 2. The distributions indicate that more than 75% data are in the interval [14, 22] for speed, and in the interval [-0.5, 0.5] for acceleration. These results demonstrate that the main characteristic of traffic on a urban throughroad is smooth driving with high vehicle speed and little speed fluctuation. The value ranges of the lead vehicle states provide us a reference for the design of the simulator test for the car-following scenario.

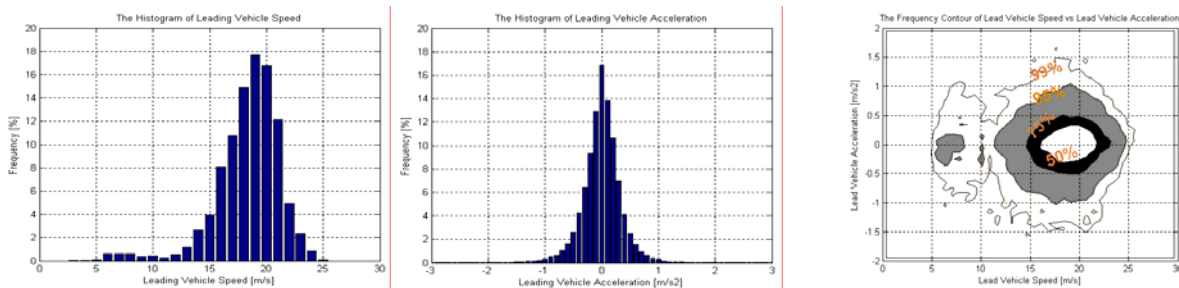


Figure 2 - Lead vehicle speed distribution (left), acceleration distribution (middle), and contour of lead vehicle speed and acceleration (right)

The lead vehicle state fluctuation influences the car-following behaviour of the host vehicle driver. Discrete Fourier transform is used to analyse the lead vehicle acceleration frequency characteristics. Figure 3 (left) shows the analysis results including 3 data segments of driver #01. These indicate that the frequencies with higher power are concentrated in the range between 0.0 to 0.5 Hz. Furthermore, all of the data segments are combined together to carry out the discrete Fourier transform to validate this characteristic, the results of which are shown in Figure 3 (right). These results could help us to design the experimental scenarios to study the response of the driver to the lead vehicle with different acceleration frequencies.

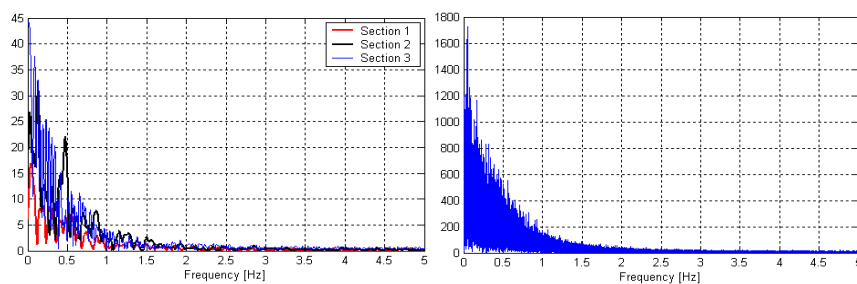


Figure 3 - Discrete Fourier Transform result of lead vehicle acceleration (left: driver #01; right: all data)

### 2.1.2. Lead vehicle scenarios

Based on the above analysis of the lead vehicle performance, two lead vehicle scenarios were proposed to study the difference between drivers in the same traffic conditions, in terms of the different lead vehicle speed characteristics. The scenarios of the lead vehicle speed are shown in Figure 4.

Scenario A: Lead vehicle runs with sinusoidal acceleration.

In this scenario, the lead vehicle runs with sinusoidal acceleration with different frequencies, of respectively 0.01, 0.02, 0.05, 0.10 and 0.20 Hz. In order to avoid large vehicle speed fluctuations, the amplitudes of the acceleration at different frequency are adjusted to keep the vehicle speeds between 16 m/s and 20m/s. The lead vehicle travelling distance is 5,654 m. The purpose of this

scenario is to investigate the driver car-following behaviour when the lead vehicle speed fluctuates at different frequencies, which also can bring the lead vehicle state closer to real-world conditions

Scenario B: Lead vehicle brake with different deceleration.

Most of the real road experimental scenarios are quite normal and safe. Few emergency situations have occurred during the experiments. However, use of the simulator is required to carry out some emergency situation experiments such as the lead vehicle braking suddenly. This work is very helpful for the understanding of driver collision avoidance behaviour. In this scenario, the lead vehicle performs a number of brake scenarios including emergency braking. The brake deceleration is set as triangle pulse and the peak values are 2, 4 and 8 m/s<sup>2</sup>. The lead vehicle speed varies between 18 and 22 m/s. The lead vehicle travelling distance is 7,572 m.

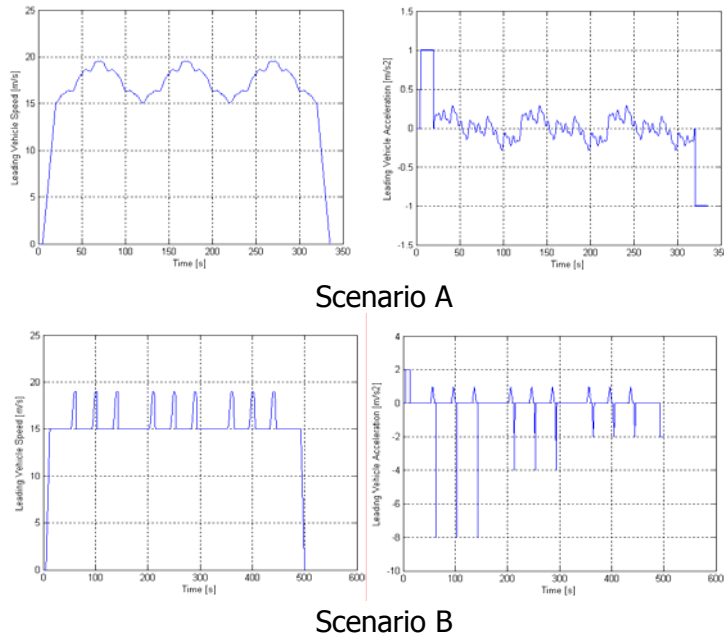


Figure 4 - Illustration of the lead vehicle speed and acceleration

## 2.2. Driver car-following tests design

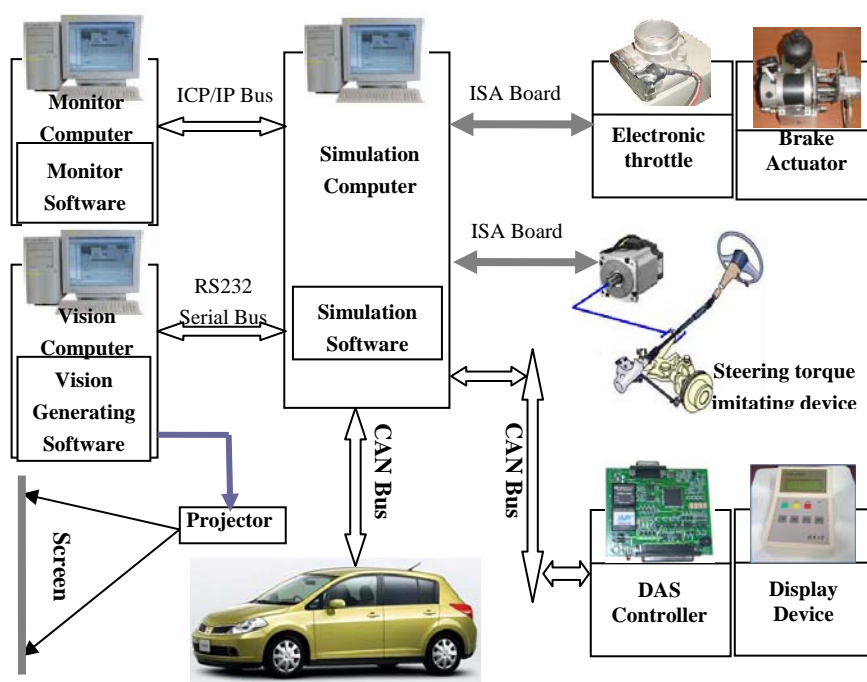


Figure 5 - System configuration of driving simulator platform [Wang, et al., 2009]

A driving simulator was developed, including a visualisation environment, hardware systems, communication modules and simulation software (see Figure 5). This simulator can provide a high-quality virtual environment which reconstructs the traffic situations and driving experience [Wang, et al. 2009].

Twenty-four participants were selected for the simulator study of longitudinal driving behaviour. All of them have a driving licence. The average age of the participants is 37.4 years (S.D. = 10.3; min = 23.0; max = 61.0). On average the participants hold their driving licenses for 8.4 years (S.D. = 7.9; min = 0.5; max = 29.0). Each driver completed the simulator tests by following the four lead vehicle scenarios. The test took about one hour for each participant. Following the designed scenarios, the simulator study is conducted in a fixed procedure, including four steps (see Table 1). Every participant followed the four-step testing procedure.

The host vehicle state data were recorded and comprehensively analysed. The simulator data provide a characterisation of the longitudinal driving behaviour and performance of the test drivers, both in normal and emergency situations.

Table 1 - Four-step testing procedure of the simulator study

Step	Description
Step 1. Introduction	The test assistant introduces the test procedure and simulator operation method to the driver.
Step 2. Trial Drive	The driver goes on board and makes a trial drive to practice the simulator's operation. The lead vehicle keeps a constant speed at 50 km/h. The driver operates the simulator freely and overtaking is permitted.
Step 3. Test of Scenario A	The assistant operates the control computer to import the lead vehicle data of Scenario A and starts the test. The driver subjects follows the lead vehicle based on his/her habit and no overtaking is permitted. When the test ends the assistant saves data and the driver subjects can rest 3 minutes.
Step 4. Test of Scenario B	The assistant operates the control computer to import the lead vehicle data of Scenario B and starts the test. The driver subjects follows the lead vehicle based on his/her habit and no overtaking is permitted. When the test ends the assistant saves data and the driver subjects can rest 3 minutes.

## 2.3 Longitudinal driving behaviour classification

### 2.3.1. Data analysis and measureable safety parameters

The two scenarios aim to investigate the car-following characteristics of the driver with different lead vehicle performances. Scenario A is considered as a following scenario close to the real world situation, because of its combined frequency composition. Scenario B is designed as an emergency brake scenario to simulate an infrequently occurred traffic situation.

In this study safety parameters are used for the longitudinal driving behaviour classification. The parameters are selected to enable objective quantification of driving style and driver characteristics. The definitions and characteristics of the selected safety parameters are presented in Table 2. The (extracted) data analysis of the safety parameters is shown in Table 3.

### 2.3.2. Category of driving behaviour and classification method

Although age, gender and driving experience are generally used to classify driving behaviour, this information is insufficient to provide adequate to determine driving style and driver characteristics because of the complicated nature of human beings. In this research, four categories of longitudinal driving behaviour are classified, where two opposite groups in every category are defined by using the measureable safety parameters (see Table 4).

These categories and groups cover the simplified features of the driving styles and driver characteristics. The terms that are used for the description of the driving style and driver characteristics are on purpose chosen in such a way that they can be expressed in terms of the defined and measurable safety parameters. For the classification of longitudinal driving behaviour, we are confronted with two issues: to identify an objective approach for data analysis; and to deal with unobvious distributions of the parameters (e.g. no explicit boundary between the data points, because the difference in driving behaviour is not very distinct). In this research, the K-means clustering algorithm [MacQueen, 1967] is selected to cope with these issues. It is an efficient algorithm to distinguish the two opposite groups in each category, based on the internal relationships between the data and the location of the centroid for each opposite group.

Table 2 - Safety parameters for the longitudinal driving behavioural classification

Symbol	Definition	Characteristics
$THW_{mean}$	mean value of the time headway for every available points which accord with aforementioned data extracted principles in Scenario A	average level of the time headway during car-following
$\sigma_{THW}$	standard deviation of the time headway for every available points in Scenario A	fluctuation level of the time headway during car-following
$\sigma_{TTCi}$	standard deviation of the time-to-collision for every available points in Scenario A	fluctuation level of the time headway during car-following
$T_{RESB}$	mean value of the elapsed time from lead vehicle deceleration start to brake activation in Scenario B	brake response time of the driver to the lead vehicle deceleration
$T_{RESA}$	mean value of the elapsed time from lead vehicle deceleration start to accelerator pedal release in Scenario B	accelerator release response time of the driver to the lead vehicle deceleration
$TTCi_B$	mean value of time-to-collision inverse at the brake activation response to the lead vehicle deceleration in Scenario B	preferred danger estimation level to trigger brake pedal activation
$TTCi_A$	Mean value of time-to-collision inverse at the accelerator pedal release response to the lead vehicle deceleration in Scenario B	preferred danger estimation level to trigger accelerator pedal release
$T_{sw}$	mean switch time from accelerator pedal release to brake activating in Scenario B	pedal switch urgency level

Table 3 - Statistic analysis results of the selected safety parameters

Parameter	Mean Value	Standard Deviation	Maximal Value	Minimal Value
$THW_{mean}$	2.7497	1.5516	0.7775	6.1915
$\sigma_{THW}$	1.6465	0.8789	0.3897	3.0546
$\sigma_{TTCi}$	0.0617	0.0252	0.0269	0.1266
$T_{RESB}$	5.5398	3.0388	1.3878	13.5350
$T_{RESA}$	4.0436	2.8310	1.0067	10.6300
$TTCi_B$	0.1708	0.1217	-0.0135	0.5042
$TTCi_A$	0.1273	0.0772	0.0258	0.3622
$T_{sw}$	3.9921	2.3795	0.4280	10.1300

Table 4 - Categorisation of the longitudinal driving behaviour by using safety parameters

Category	Measureable safety parameters	Group A	Group B
1. Prudence	$THW_{mean}$ , $T_{sw}$	aggressive	prudent
2. Stability	$\sigma_{THW}$ , $\sigma_{TTCi}$	unstable	stable
3. Safety-mindedness	$TTCi_B$ , $TTCi_A$	risk prone	safety prone
4. Skilfulness	$T_{RESB}$ , $T_{RESA}$	non-skilful	skilful

K-means clustering can be described as a partitioning method and is suitable for clustering large amounts of data. The K-means algorithm treats each observation in the data as an object having a location in space. It finds a partition in which objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. Each cluster in the partition is defined by its member objects and by its centroid. The centroid for each cluster is the point for which the sum of distances from all objects in that cluster is minimised. K-means uses an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid, over all clusters. This algorithm moves objects between clusters until the sum cannot be decreased further. The result is a set of clusters that are as compact and well-separated as possible.

### 3. RESULTS

#### 3.1. Prudence: aggressive vs. prudent driver behaviour

It is considered that the prudent driver behaviour prefers higher  $T_{SW}$  to give himself more time to estimate the danger state. The parameter pair  $[THW_{mean} T_{SW}]$  are normalised to  $[-1 1]$ . Figure 6 (left) shows the classification result to this parameter pair with K-means algorithm. Figure 6 (right) shows the silhouette plot of this cluster classification. The mean value of the silhouette values, which is 0.4117, is an acceptable result. The normalised parameter data are classified into 2 groups clearly. The values of the two centroids indicate that Group A has smaller following time headway and smaller switch time, and can represent the group of aggressive driver behaviour, and the Group B can represent the group of prudent driver behaviour. The centroid of Group A  $[-0.562, -0.282]$  can be converted to time headway and switch time dimensions as  $[1.962, 3.910]$ . The centroid of Group B  $[0.374, -0.097]$  can be converted to time headway and switch time dimensions as  $[4.497, 4.810]$ .

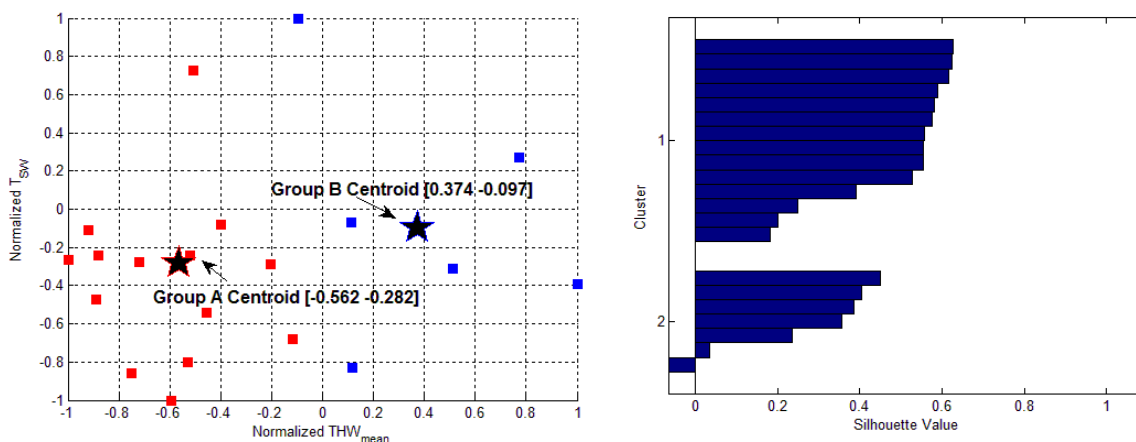


Figure 6 - Classification result of Category 1 (left), and silhouette plot of Category 1 classification (right)

#### 3.2. Stability: unstable vs. stable driver behaviour

$[\sigma_{THW} \sigma_{TTC}]$  are selected as the parameter pair of this category. The parameters are also normalised to  $[-1 1]$  before classification. Figure 7 (left) shows the classification result to this parameter pair with K-means algorithm. Figure 7 (right) shows the silhouette plot of this cluster classification. The mean value of the silhouette values, which is 0.4821, is acceptable. The results show a reasonable cluster classification that the normalised parameter data are classified into 2 groups clearly. The values of the two centroids indicate that the two parameters of Group A are greater and can represent the unstable driver group and the Group B can represent the stable driver group. The centroid of Group A  $[0.797, -0.264]$  can be converted to time headway and time-to-collision dimension as  $[2.784, 0.063]$ . The centroid of Group B  $[-0.461, -0.519]$  can be converted to time headway and time-to-collision dimension as  $[1.108, 0.051]$ .

### 3.3. Safety-mindedness: risk prone vs. safety prone driver behaviour

As the driver classification with real traffic data, the parameter pair  $[TTC_i, TTC_b]$  are also selected

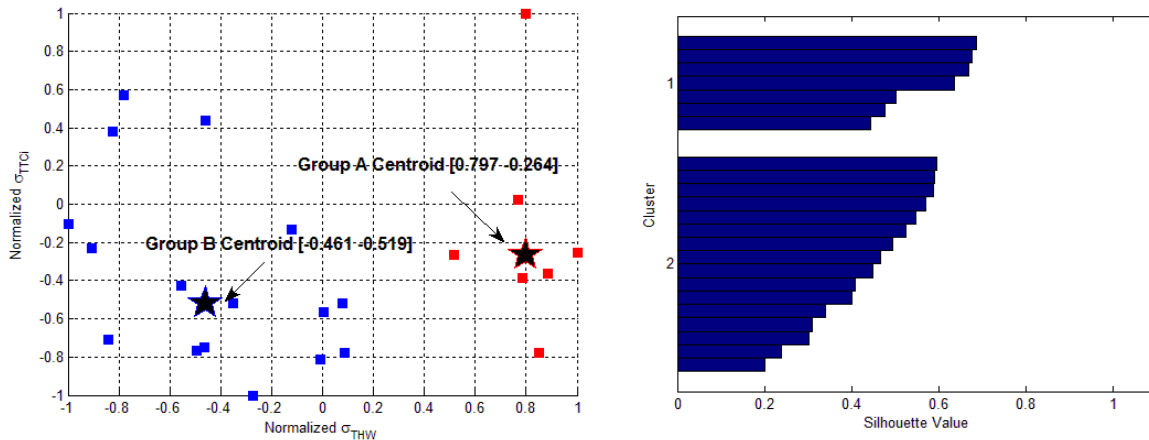


Figure 7 - Classification result of Category 2 (left), and silhouette plot of Category 2 classification (right)

to represent the driver safety tendency in this category classification. The parameters are also normalised to  $[-1 \ 1]$  before classification. Figure 8 (left) shows the classification result to this parameter pair with K-means algorithm. Figure 8 (right) shows the silhouette plot of this cluster classification. The mean value of the silhouette values, which is 0.5362, is acceptable. The results show a reasonable cluster classification. The normalised parameter data are classified into 2 groups clearly. The values of the two centroids indicate that the two parameters of Group A are much greater, which means that the drivers of Group A choose smaller time-to-collision to avoid collision. This result shows that this parameter pair can classify the risk prone driver group and safety prone driver group. There are 11 driver subjects locating into Group A and the number of Group B is 11. The centroid of Group A  $[0.004, -0.173]$  can be converted to TTC inverse dimension as  $[0.247 \ 0.165]$ . The centroid of Group B  $[-0.638, -0.704]$  can be converted to TTC inverse dimension as  $[0.080 \ 0.076]$ .

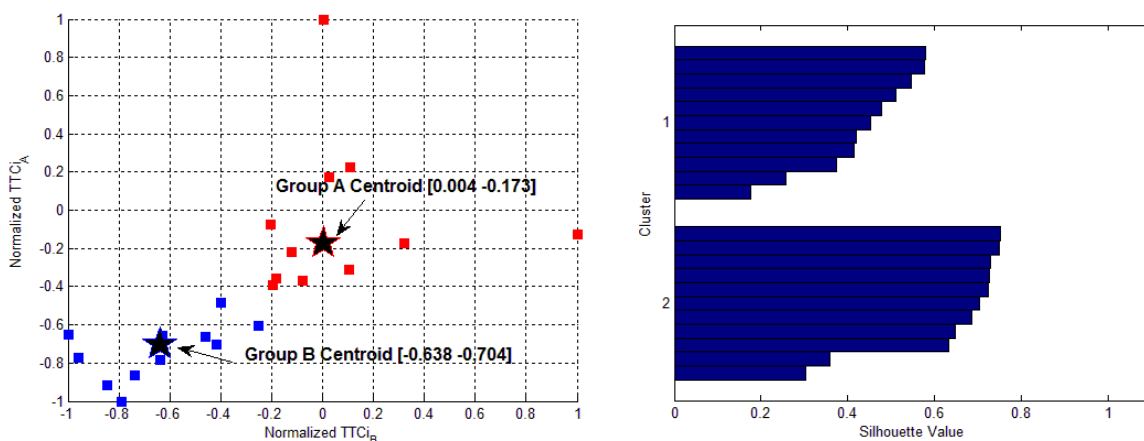


Figure 8 - Classification result of Category 3 (left), and silhouette plot of Category 3 classification (right)

### 3.4. Skilfulness: non-skilful vs. skilful driver behaviour

It is difficult to estimate a driver whether is a non-skilful driver or skilful driver. In the classification of simulator test data, two new parameters,  $T_{RESB}$  and  $T_{RESA}$ , are applied to give an understanding of the driver experience degree from another viewpoint. It is supposed that the non-skilful driver has smaller elapsed time from leading vehicle deceleration start to accelerator pedal release and

brake pedal activation because of nervous psychosis and the lack of driving skill. The parameter pair  $[T_{RESB} T_{RESA}]$  are also normalised to  $[-1 1]$  before classification. Figure 9 (left) shows the classification result to this parameter pair with K-means algorithm. Figure 9 (right) shows the silhouette plot of this cluster classification. The mean value of the silhouette values, which is 0.5762, is acceptable. The results show a reasonable cluster classification. The normalized parameter data are classified into two groups clearly. The values of the two centroids indicate that the parameters of Group A are smaller, which means that the drivers of Group A choose smaller elapsed time from leading vehicle deceleration start. This result shows that this parameter pair can classify non-skilful driver group and skilful driver group. There are 13 driver subjects locating into Group A and the number of Group B is 8. The centroid of Group A  $[-0.676, -0.769]$  can be converted to acceleration dimension as  $[3.357, 2.120]$ . The centroid of Group B  $[-0.000, 0.230]$  can be converted to acceleration dimension as  $[7.461, 6.926]$ .

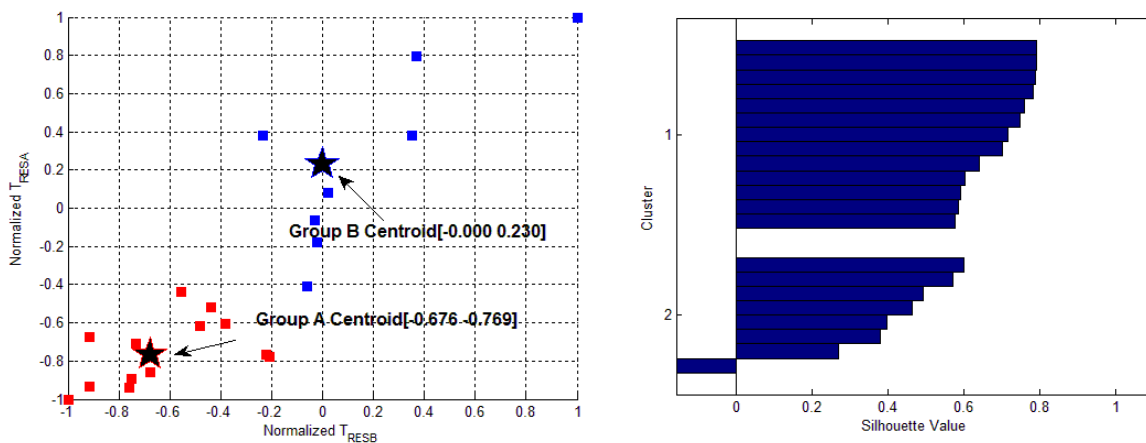


Figure 9 - Classification result of Category 4 (left), and silhouette plot of Category 4 classification (right)

#### 4. CONCLUSIONS AND FUTURE WORK

In this paper the classification of the dissimilarity of the longitudinal driving behaviour is further investigated by using simulator study. Approaches were designed to make lead vehicle scenarios, and to identify main determinants of longitudinal driving behaviour by using measurable safety parameters from the perspective of automotive engineering. It shows that the driver behaviour could be characterised by using measurable safety parameters related to THW, TTC, elapsed time (from lead vehicle deceleration start to brake activation, and from lead vehicle deceleration start to accelerator pedal release), TTCi (at the brake activation response to the lead vehicle deceleration, and at the accelerator pedal release response to the lead vehicle deceleration), and switch time (from accelerator pedal release to brake activating).

K-means clustering algorithm is used in this research. The results show that the algorithm is an efficient and simple for clustering. The results from the simulator study have also been compared with those from our previous study on the characterisation of longitudinal driving behaviour using real world data [Lu, et al, 2010]. Both studies conclude that the dissimilarities in the longitudinal driving behaviour can be classified by driving style and characteristics, i.e. longitudinal driving behaviour is classified as the pairs of driver groups in four main determinants using measurable safety parameters: prudence (aggressive vs. prudent), stability (unstable vs. stable), safety-mindedness (risk prone vs. safety prone), and skilfulness (non-skilful vs. skilful).

In addition, the validity of our developed driving simulator for the longitudinal driving behavioural study has been confirmed. The research result is helpful for the development of active safety systems by taking the driving behaviour into account.

More experiments will be done in the simulator, and the classified results of driver characteristics

will be further evaluated by real world experiments, comparative analysis will be carried out of the differences of the driving behaviour in the driving simulator and the real world environment in future work.

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