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Multi-parameter prediction of drivers' lane-changing behaviour with neural network model

Jinshuan Peng [a,*], Yingshi Guo [b], Rui Fu [b], Wei Yuan [b], Chang Wang [b]

[a] Chongqing Key Lab of Traffic System & Safety in Mountain Cities, Chongqing Jiaotong University, Chongqing 400074, China
[b] Key Laboratory of Automotive Transportation Safety Technology, Ministry of Transport, Chang'an University, Xi'an 710064, China

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ABSTRACT

Accurate prediction of driving behaviour is essential for an active safety system to ensure driver safety. A model for predicting lane-changing behaviour is developed from the results of naturalistic on-road experiment for use in a lane-changing assistance system. Lane changing intent time window is determined via visual characteristics extraction of rearview mirrors. A prediction index system for left lane changes was constructed by considering drivers' visual search behaviours, vehicle operation behaviours, vehicle motion states, and driving conditions. A back-propagation neural network model was developed to predict lane-changing behaviour. The lane-change-intent time window is approximately 5 s long, depending on the subjects. The proposed model can accurately predict drivers' lane changing behaviour for at least 1.5 s in advance. The accuracy and time series characteristics of the model are superior to the use of turn signals in predicting lane-changing behaviour.

1. Introduction

Lane-changing behaviour has a significant effect on driving safety and the stability of traffic flow (Sivak et al., 2007). During the lane-changing process, the information processed by the drivers is more complicated than that processed while remaining in a lane. If drivers fail to accurately judge the appropriate lane-change time or the relative movement characteristics of related vehicles, accidents may occur and result in casualties and property damage (Petzoldt et al., 2014; Jin, 2013).

Various of lane-change auxiliary systems have been developed in an attempt to ensure driver safety during the lane-changing process. Such systems operate by monitoring the related conflict vehicles with millimetre-wave radar or high-accuracy cameras. Once turn signals are recognized, the auxiliary system may assume that a lane change will be executed at some time in the near future, and the system enters its working mode. When a conflict object is detected by the auxiliary system within a given distance, warning signals are sent to remind the drivers of the potential danger (Hirose et al., 2004). However, in practice, prediction of lane-changing behaviour on the basis of turn signals is unreliable. According to the experiment conducted under realistic on-road conditions, the operation rate of drivers' turn signals is below 50% by the initiation of the lane changing behaviour, which certainly affects the warning accuracy rate and reliability of a lane-changing auxiliary system that is triggered by turn signals (Salvucci and Liu, 2002).

In recent years, researchers have pursued ways to improve the performance of lane-changing auxiliary systems by identifying drivers' operation intentions. Specifically, researchers have tried to identify lane-changing intent via drivers' visual search behaviours and vehicles' motion characteristics. Based on gaze data of interest zones, Lethaus et al. (2013) predicted drivers' driving intent via compound model, and in their previous research, they have proved that drivers may pay more attention to side mirrors than to inside mirrors when executing leftward lane changes (Lethaus and Rataj, 2007). Salvucci et al. (2007) suggested that before a lane change occurred, a driver always shifted attention from the current lane to the target lane. Doshi and Morris (2011, 2009) proposed that in addition to eye movements, head movements could be used to detect drivers' lane-changing intentions, and developed a real-time on-road prediction system to detect driver's intention. Peng et al. (2013a,b) constructed an intent index system by analysing the differences between lane keeping and lane changing intent stages, and developed a method to detect drivers' lane-changing intentions using evidence theory.

* Corresponding author. Tel.: +8618223599639.
E-mail address: pengjinshuan@163.com (J. Peng).

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If drivers' lane-changing intentions could be precisely identified from their driving behaviour, rather than relying on turn signals, the performance of lane-changing assistance systems could be greatly improved. However, challenges arise in the practical application of lane-changing intent identification technologies. Although an assistance system may detect a driver's intent to change lanes, this does not mean that a lane change will definitely occur at some time in the future. Even if a driver intends to execute a lane change, he may change his mind for various reasons, such as a vehicle rapidly approaching from behind in the target lane. We call this the "intent revocation phenomenon", and it cannot be easily predicted using the existing intent identification technologies (Lee et al., 2014; Hofmann et al., 2010).

Lane-changing intent can typically be detected from a driver's eye and head movements before the execution of a lane change (Lethaus and Rataj, 2007). Based on intent identification, if we could consider vehicle motion states and the relative motion between the object vehicle and other (conflict) vehicles in a comprehensive manner, we may be able to predict lane-changing behaviour accurately before the manoeuvre.

This study was conducted to develop a reasonable method for predicting lane-changing behaviour. The remainder of the paper is organized as follows. First, the testing platform and experimental design are presented. Second, the procedure used to select lane changing intent and lane keeping data samples is described, along with the procedure used to determine the lane changing intent time window. Third, lane-changing behaviour predictors are identified based on eye and head movement characteristics, in combination with information on the relative motion of conflict vehicles. Finally, the use of a neural network to develop a model for real-time prediction of lane-changing behaviour is described.

2. Experiment

2.1. Subjects

A total of 16 experienced drivers, nine men and seven women, were recruited to take part in our experiment. The subjects were between the ages of 28 and 50, with an average age of 41.1 years and a standard deviation of 5.85 years. Each of the subjects had got a driver's licence for at least four years and had driven a total distance of at least 80,000 km. The drivers participated in physical fitness examinations that showed that all of the subjects were free from any visual, physical, or psychological impairment and could meet the demands of the experiment. After the experiment, the subjects were reimbursed for a certain amount of their lost income.

2.2. Procedure

Due to the convenience and simplicity of simulation experiment, research on drivers' behaviour characteristics is typically conducted using driving simulators (Lee et al., 2014; Salvucci et al., 2007). However, simulations do not reflect the effect of the surrounding environment as well as naturalistic on-road driving tests. As a result, experimental results obtained from simulation often fail to represent drivers' real behavioural characteristics (Dziuda et al., 2014; Jagannath and Balasubramanian, 2014). To address this problem, we built an integrated data collection platform to acquire information on drivers' behavioural characteristics, vehicle motion status, etc. The experiment was conducted as a naturalistic driving test: each driver was told to drive completely according to his or her own driving expectations, habits, and real-time judgement of the conditions of the surrounding environment.

Before the experiment was run, the drivers first provided personal information by filling out a form developed by the research team. The team calibrated the instruments based on the coordination of the subjects. The subjects each had 15 min to familiarize themselves with the testing vehicle and were told about the testing route. Then, after a 10-min break, the naturalistic on-road experiment began.

2.3. Test platform

To achieve our research objective of developing a model for prediction of lane-changing behaviour, we needed to collect data on the vehicle motion states, driving environment, and the drivers' behaviours. The integrated data collection platform developed for this purpose included the following sensors and instruments: a faceLAB 5 eye tracking system (for tracking eye and head movements), a VBOX (for recording vehicle velocities, lateral accelerations, longitudinal accelerations, yaw rates, etc), millimetre-wave radars (for measuring the relative motion between the object vehicle and conflict vehicles), a lane identification system (for recording the lateral position of the vehicle in the lane), a torque sensor (for measuring the steering wheel angle and steering angular velocity), and a data acquisition meter. The system components are shown in Fig. 1.

2.4. Test route

The objective of this study is to develop a prediction model for lane-changing behaviour for use in a lane-changing assistance system. In general, such a system is activated when the speed of the vehicle reaches approximately 50 km/h (Wang et al., 2014). To enhance the practical applicability of the research results, we chose to locate our test route on the G25 expressway (from Huzhou to Changxing, Zhejiang, China), which was a two-way four-lane road with a speed limit of 110 km/h. The length of the portion of the expressway used as the test route was approximately 25 km.

3. Lane-changing intent time window

3.1. Initiation of a lane change

The selection of the lane change sample is a key step in the development of the behaviour prediction model. The complete lane-changing process can be divided into several stages, as shown in Fig. 2. The most urgent problem to be solved is determination of the initiation of a lane change. To avoid the subjectivity of the existing methods (Huo, 2010), we develop a new method for determining the initiation of a lane change as a function of the lateral position of the vehicle in the lane and the steering wheel angle.

The sampling frequency of the data collection system is 10 Hz. The distances from the left front wheel and right front wheel to the left lane and the right lane, respectively, are denoted by L_1 and L_2, as shown in Fig. 3. Table 1 shows a portion of the data for a lane change, illustrating the changes in the lateral position of the vehicle and the steering wheel angle over time. According to Table 1, the lateral position of the vehicle change slightly between the adjacent sampling times in the lane keeping stages. However, when the effects of the vehicle's lateral position and steering wheel angle are considered, the rate of change obviously increase during the sampling time highlighted in grey, so this is considered to be the moment of initiation of the lane change (as shown in Fig. 4).

3.2. Determination of lane changing intent time window

As other researchers have shown, in comparison to lane keeping behaviours, drivers tend to exhibit distinct eye and head movement characteristics before changing lanes (Hsu and Liu, 2008; Olsen

Fig. 1. Components of the data collection platform.

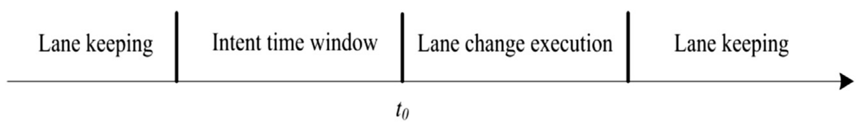

Fig. 2. Stages division of the lane-changing process (t_0 is the initiation of a lane change manoeuvre).

et al., 2005; Lethaus and Rataj, 2007). This paper proposes a method to determine the lane changing intent time window from a driver's eye movements with respect to the rearview and sideview mirrors.

In Worldview software of Facelab systems, according to the relative position between the testing vehicle and related interest areas (rearview and sideview mirrors, dashboard, front vision, and so on), corresponding Worldview models are established, then distribution of the fixation points at any time could be obtained. For one lane change, it is assumed that the driver's fixation frequency on the rearview and sideview mirrors is a natural number N (where, in general, $N \geq 1$). The time of the first fixation on the

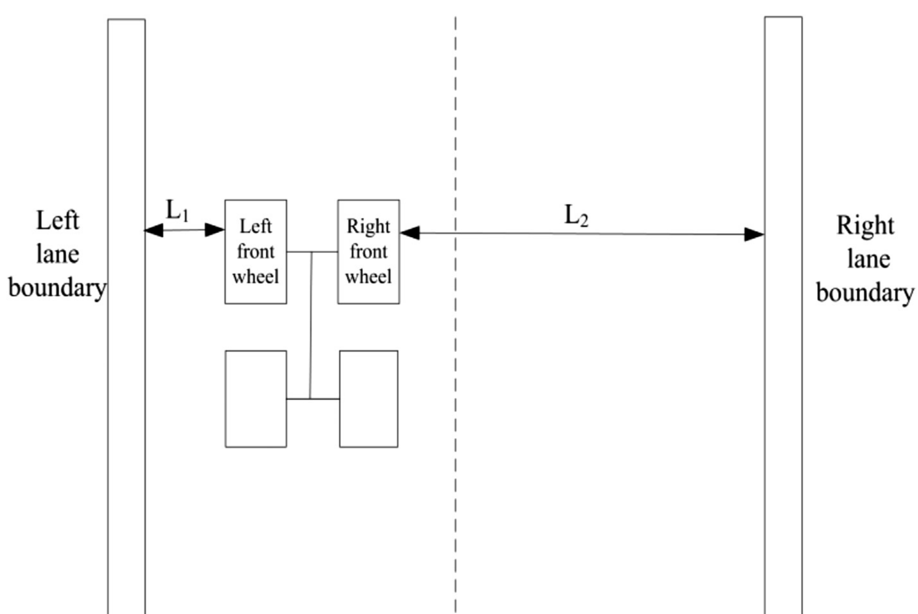

Fig. 3. Lateral position of the vehicle in the lane.

Table 1
Lateral position and steering wheel angle during a left lane change (data segment).

Sampling time	L_1 (cm)	L_2 (cm)	Steering wheel angle (°)
13:53:16	−110	70	5.953
13:53:16	−110	70	5.483
13:53:16	−110	70	5.127
13:53:16	−115	65	4.985
13:53:16	−115	65	5.012
13:53:16	−115	65	4.487
13:53:16	−110	70	4.256
13:53:16	−110	70	4.463
13:53:16	−110	70	4.504
13:53:16	−110	70	4.472
13:53:17	−90	90	4.458
13:53:17	−90	90	5.551
13:53:17	−75	105	6.953
13:53:17	−65	115	7.874

Shades signifies lane change initiation.

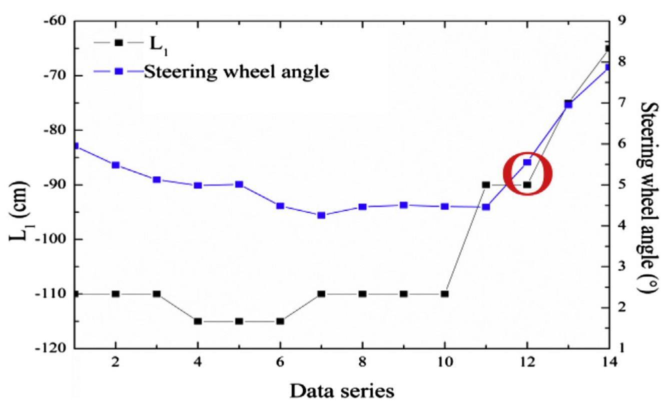

Fig. 4. Determination of the moment of Lane change initiation.

rearview mirror is defined as t_0. Using the method proposed in section 3.1, the initiation of the lane change sample can be determined, and the time difference between the two (the time of first fixation and the moment of lane change initiation) can be considered the lane-changing time window of a sample. Using this method, we are able to obtain the distribution of lane-changing time windows for all of the subjects, as shown in Fig. 5.

Fig. 5 shows that the 75th percentiles of the time windows for most of the subjects are less than 5 s, as indicated by the dotted line in the figure. A single-factor analysis of variance is conducted to determine whether significant differences existed among the intent time windows of the subjects. The results ($F = 0.923 < F_{0.05}(15,213) = 1.67$) show that no significant differences existed. This finding suggests that the method used in this study could provide a theoretical basis for determining a unified time window length. And Fig. 5 shows that the median intent time window length for the subjects ranges from 2 to 4.5 s. To avoid loss of data for the lane-changing intent stage, we ultimately select 5 s as the length of the lane changing intent time window.

Prior to establishing a forecasting index for lane-changing behaviour, we first have to select the lane keeping and lane-changing intent samples. After the on-road experiment was conducted with each driver, we examined video recorded during the experiment, together with the experimental data collected. We classified the drivers' driving behaviours during the experiment as specific processes, such as lane changing, car following, free driving in the current lane, etc. Car following, free driving and driving behaviours before lane changing intent stages were selected as lane keeping samples, and the selection was a random process. Based on the lane changing intent time window length as described above, combined with the method for determining lane change initiation described in Section 3.1, the lane changing intent samples could also be selected. For convenience in comparing the driving behaviours associated with different driving processes, all the lane keeping and lane changing intent samples were 5 s in duration.

Using the method described above, we selected 401 lane keeping samples and 406 lane changing intent samples. From each of these two groups, 200 samples were selected as training samples, and the others were left for use as samples to be predicted. It is important to note that the faceLAB system is installed in front of the driver, on the condition that the driving seat is in left side, the lateral measurement range of faceLAB is not wide enough to capture the driver's fixation points dwelling at the far right, such as the right sideview mirror. Given this restriction, only changes from the right lane to the left lane are analysed in this study.

4. Predictive index

4.1. Eye and head movements

Previous studies have shown that eye and head movements are the most important characteristics in predicting a driver's lane-changing intent (Gurupackiam and Jones, 2012; Henning et al., 2007; Pech et al., 2014). To reflect the differences in drivers' visual search behaviours in the different driving stages, gaze angle distributions of the training samples selected from the lane keeping and lane changing intent sample sets are represented by the heat maps, as shown in Figs. 6 and 7. The heat maps are derived based

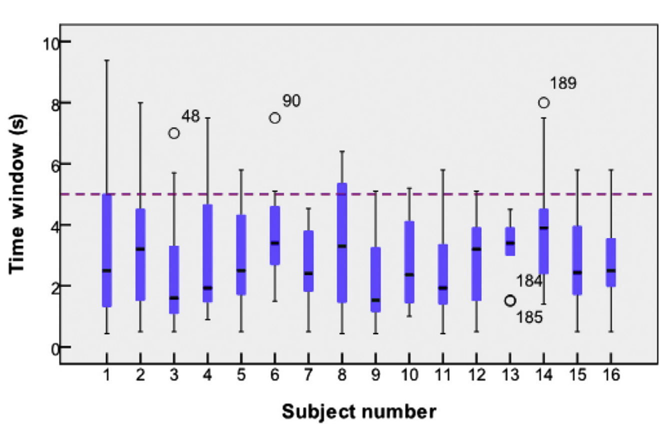

Fig. 5. Overall distribution of lane changing intent time windows for the subjects.

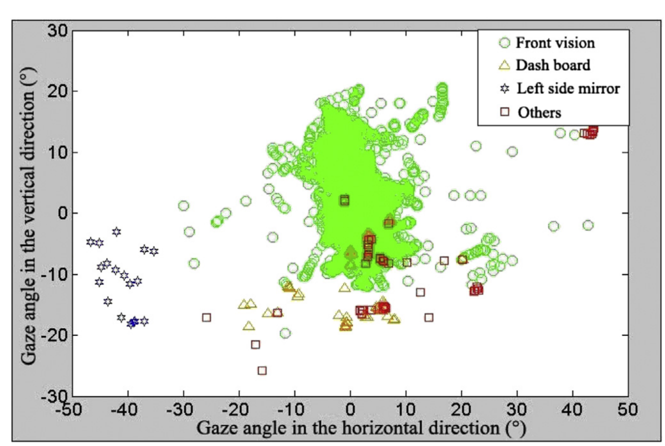

Fig. 6. Gaze angle distribution during lane keeping stage.

upon 200 lane keeping training samples, as well as 200 lane changing intent samples, respectively. Given the sampling frequency of faceLAB system in the collection platform is 30 HZ, so there exists 150 sampling points for one certain training sample.

The definition of the gaze angle is illustrated in Fig. 8. The difference of the gaze angles in the vertical direction between the lane changing intent stage and the lane keeping stage is not significant. However, the difference in the horizontal direction is significant and indeed remarkable. During the lane keeping stage, drivers tend to focus primarily on objects in front of them, including dynamic targets in the current lane and the target lane and other targets of interest, and to focus less on other objects, such as the dashboard and the left sideview mirror (Beggiato and Krems, 2013; McCall et al., 2007). However, during the lane changing intent stage, drivers tend to focus more on the dashboard and the left sideview mirror. These differences in focus arise before changing lanes because drivers need to pay more attention to the side mirrors to obtain motion states information of conflict vehicles in their rear view, as well as their vehicle's speed (Salvucci et al., 2007; Oh and Kim, 2010) to select the acceleration or deceleration behaviours needed to avoid the potential traffic conflicts.

The coordination of head and eye movements is essential to accomplishing the visual search process while driving (Doshi and Trivedi, 2009; Zheng et al., 2013; Schmidt et al., 2014). If the head remains stationary and a driver relies only on eye movements, the driver's visual search scope is very small. Attention is mainly concentrated on objects directly in front of the driver, who fails to clearly observe objects in the far right, far left and rear, which may lead to a collision. To enlarge the visual search scope, head movements must be made to increase the range of the eye movements (Zhou et al., 2009; Kiefer and Hankey, 2008). In fact, the gaze angle (ϕ_e) parameter is synthesized by the head rotation angle (ϕ_h) and the eyeball's rotation angle relative to the head (ϕ'), as shown in Equation (1).

$$\phi_e = \phi_h + \phi' \tag{1}$$

Henning et al. (2007) suggested that head movements could reflect a driver's lane-changing intent earlier than eye movements. This suggestion was confirmed in a follow-up study by Doshi et al. (2011). Based on this finding, we tried in this study to characterize drivers' lane changing intentions via the standard deviation of the head rotation degree (Std of HRD) in the horizontal direction. Fig. 9 shows the head movement parameters in a global coordinate system in which the head yaw corresponds to the head rotation degree in the horizontal direction. The distributions of the Std of HRD in the horizontal direction during the lane keeping and lane changing intent stages (over 5 s period) are shown in Fig. 10. These

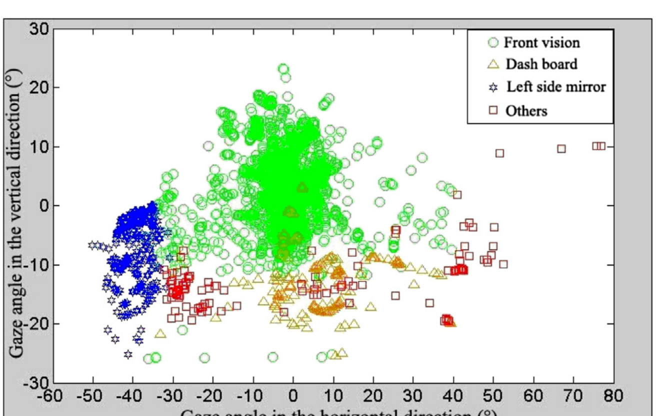

Fig. 7. Gaze angle distribution during lane changing intent stage.

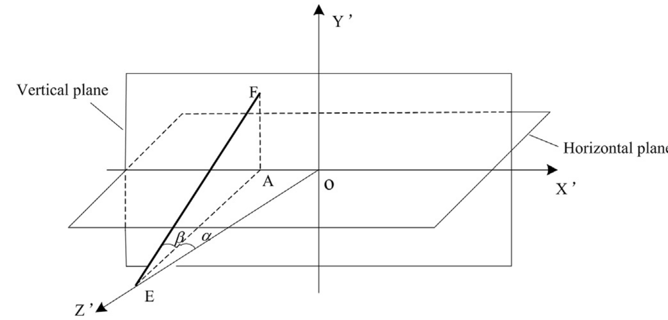

Fig. 8. Illustration of gaze angle definition. E is the position of the eyeball, F is a fixation point, A is the projection of F onto a horizontal plane, EF is the sight line, α is the gaze angle in the horizontal direction, and β is the gaze angle in the vertical direction.

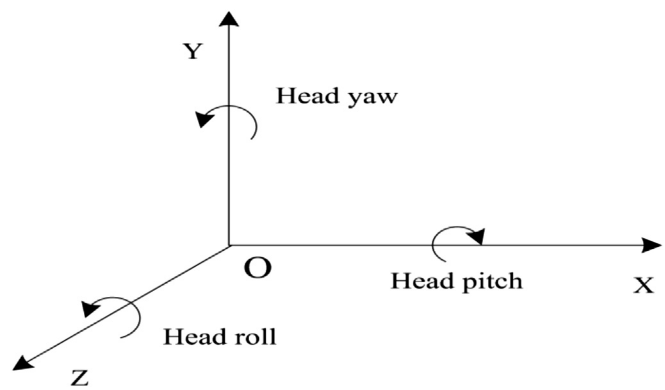

Fig. 9. Head rotation degree parameters in the global coordinate system.

distributions clearly show that the Std of HRD for the lane changing intent samples is considerably larger than that for the lane keeping samples ($p < 0.05$). The average values of the Std of HRD for the lane keeping and lane changing intent samples are 1.6° and 8.9°, respectively.

4.2. Vehicle motion states and driving conditions

To some extent, the use of turn signals can serve as an indicator of a driver's lane-changing behaviour. However, this parameter is not reliable enough to yield accurate predictions when used alone (Naranjo et al., 2008; Nishiwaki et al., 2008). Based on the results of the on-road experiment, the turn signal use rate (for all lane-change samples) in time series is determined using automobile

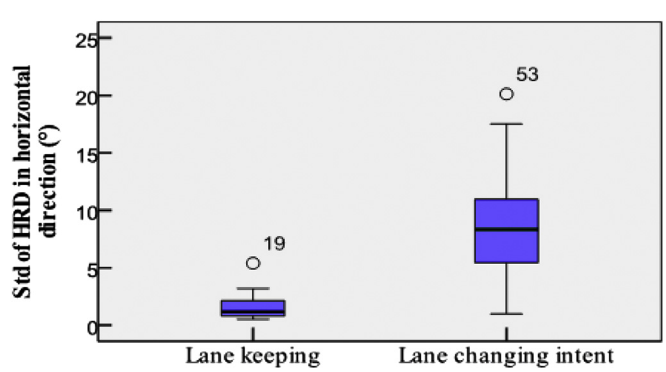

Fig. 10. Distributions of standard deviation of head rotation degree in the horizontal direction over 5 s period.

CAN-bus technology. The results are shown in Fig. 11. The coordinate origin represents the moment of initiation of the lane change (t_0). The data reveals that the turn signal use rate is approximately 48.4% by time t_0, and even 5 s after lane change execution, the use rate is still less than 80%. Therefore, turn signals can only be regarded as a useful predictor of lane changing intent when used together with other parameters.

It has been proven that different drivers exhibit different velocity control patterns when changing lanes (Tomar and Verma, 2012; Lee et al., 2004). However, for a given driver and a given set of lane-change conditions, the velocity of the car could reflect the driver's lane-changing intent (Lv et al., 2013; Mar and Lin, 2005). Vehicle velocity, like turn signal use, is not an adequate predictor on its own; we need to consider other characteristic parameters as well.

Whether a lane change will occur is influenced by other cars nearby, as shown in Fig. 12. As other researchers have shown, the leading car in the current lane and the following car in the target lane are the most influential factors to affect the lane-changing behaviour of the object car. Thus, the relative motion parameters between H_1 and the conflict cars H_2, H_3 can be considered the key indicators in predicting lane-changing behaviour (Patire and Cassidy, 2011; Toledo-Moreo and Zamora-Izquierdo, 2009).

Whether the driving environment meets the requirements for executing a lane change depends mainly on two conditions, namely, the merging gap acceptance and the time to collision (*TTC*), which is obtained by dividing the distance by the relative speed between the conflict cars. Both the merging gap acceptance and the *TTC* must be sufficiently large to ensure the safety of the lane change manoeuvre. To be useful in the prediction, the predictor must be comparable and measurable. The characteristic index system for lane change prediction shown in Table 2 is constructed by combining visual search characteristics, handing characteristics and driving conditions.

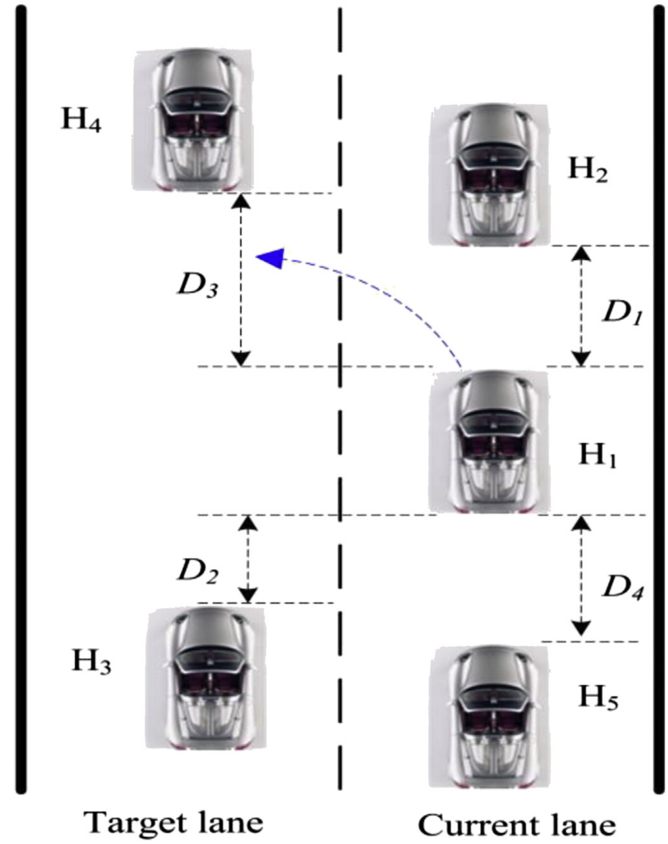

Fig. 12. Typical lane-changing scenario. H_1 is the object car that may execute a lane change manoeuvre; H_2 and H_4 are the leading cars in the current lane and target lane, respectively; H_3 and H_5 are the following cars in the target lane and current lane, respectively; and D_i ($i \in [1,4]$) is the set of relative distances between the object car and these other cars.

5. Back-propagation (BP) neural network model construction

5.1. BP network design

5.1.1. Network structure determination

The number of dimensions of the input and output layers of the BP network is determined on the basis of the requirements of an individual user or application (Kocadağlı and Aşıkgil, 2014). In principle, the number of nerve cells of the input layer is equal to the number of characteristic index parameters. Based on the characteristic index parameters shown in Table 2, the number of dimensions of the input layer is selected to be seven. In contrast, the number of dimensions of the output layer is determined by the classification of the prediction results. For the lane-change prediction problem, the prediction results (defined as event Z) can be divided into two categories: lane changing ($Z = 1$) and lane keeping ($Z = 0$). Therefore, the number of dimensions for the output layer is one.

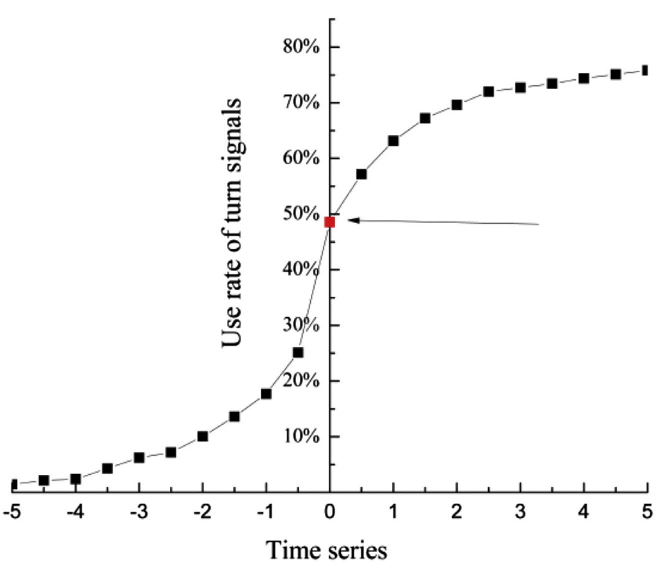

Fig. 11. Use rate of turn signals in time series.

Any continuous function defined in a closed interval can be approximated via a BP network with one hidden layer (Ozcan and Arik, 2014). In this study, we adopt a three-layer BP network containing one hidden layer to learn the training samples. The output vector is $T(Z)$, and the input vector is organized as shown in Equation (2). The input–output mode is shown in Table 3.

$$P_0 = (V_1, TS, D_1, TTC_1, D_2, TTC_2, \theta) \tag{2}$$

It is important to note that for lane changing intent samples, input vectors of the transient variables (V_1,TS,D_1,TTC_1,D_2,TTC_2) are the characteristic parameters at the time t_0 (initiation of a lane-change manoeuvre). Similarly, for the transient variables of lane keeping samples, the input vectors correspond to the cut-off time of the samples. However for the steady state variable θ during a certain time interval, given one training sample, standard deviation of head rotation degree in the horizontal direction over 5 s period is served as the input vector, for purpose of simplifying the calculation process. The number of hidden-layer neurons in the three-

Table 2
Characteristic index for lane change prediction.

Characteristic attribute	Index name	Definition of the index
Vehicle motion state	V_1	Speed of the object car (km/h)
Handling characteristics	TS	Use of turn signal (0–1 classification variables: "1" corresponds to "on"; "0" corresponds to "off")
Driving conditions	D_1	Distance between H_1 and H_2 (m)
	TTC_1	Time to collision between H_1 and H_2 (s)
	D_2	Distance between H_1 and H_3 (m)
	TTC_2	Time to collision between H_1 and H_3 (s)
Head movement	θ	Std of HRD in the horizontal direction (°)

Table 3
Input–output mode of the BP network.

Sample number	Input vector	Target output	Prediction result
1	[64.02, 1, 14.145, 60.4, 30, 25.6, 9.744]	$z = 1$	Lane change
2	[62.94, 0, 16.243, 81.7, 30, 22.5, 2.755]	$z = 0$	Lane keeping
3	[71.49, 1, 12.255, 62.5, 30, 37.6, 5.792]	$z = 1$	Lane change
4	[64.02, 0, 30, 155.9, 30, 59.9, 4.462]	$z = 0$	Lane keeping
……	……	……	……

layer BP network can be determined based on Equation (3), where n_2 is the number of hidden-layer neurons and n_1 is the number of dimensions of the input layer (Ren and Chen, 2006). While $n_1 = 7$, we may infer that $n_2 = 15$.

$$n_2 = 2n_1 + 1 \quad (3)$$

5.1.2. Transfer function

After the data are preprocessed, all of the input vectors vary between 0 and 1, so an S-type tangent function (tansig) may be regarded as the nerve cell transfer function of the hidden layer. Similarly, given that the network output is 0–1 binary variables, an S-type tangent function (logsig) serves as the nerve cell transfer function of the output layer. The trainlm function is applied with a fast convergence rate to conduct the sample training. The computing method used is the Levenberg–Marquardt back-propagation algorithm (Xiao et al., 2009; Singh et al., 2013).

5.2. Data preprocessing

5.2.1. Data normalization

If the original data of the input vector possess a high degree of dispersion, larger parameter values will occupy the learning process of the neural network. This is likely to affect the prediction accuracy of the neural network (Akbari et al., 2012). To improve the neural network training efficiency, data normalization must be carried out, as shown in Equation (4). In this equation, x corresponds to original data; y corresponds to the object data after normalization; $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of the original data, respectively; $y_{\max}$ and $y_{\min}$ are the maximum and minimum values of the data after normalization, respectively. Based on the characteristics of lane change prediction, $y_{\max} = 1$ and $y_{\min} = 0$.

$$y = (y_{\max} - y_{\min})*(x - x_{\min})/(x_{\max} - x_{\min}) + y_{\min} \quad (4)$$

5.2.2. Vacancy assignment

A slow lead vehicle in the current lane may reduce driver's satisfaction with the speed of movement and space available, so the speed of the lead vehicle in the current lane is the primary factor in inducing lane-changing behaviour of the object car (Young et al., 2011). In this study, the relative speeds and distances between the conflict cars are collected using millimetre-wave radars, the maximum range of which is approximately 200 m. For the prediction index shown in Table 2, for D_1 and TTC_1, there are two conditions for which vacancy assignment need to be conducted. The first condition exists when the distance between related conflict cars exceeds the measurement range of the millimetre-wave radars (or when conflict cars are not present). The second condition exists when the speed of H_2 is greater than that of H_1. The vacancy assignment method for D_1 and TTC_1 is shown in Fig. 13. Vacancy assignments for D_2 and TTC_2 are performed using a similar method.

5.3. Model training and performance examination

During the model training process, the feature vector (V_1,TS,D_1,TTC_1,D_2,TTC_2,θ) at time t_0 is considered the input vector P_0, and $T(Z)$ is considered the target output vector. For lane-changing behaviour, $T(Z) = 1$, while for lane keeping behaviour, $T(Z) = 0$. Two hundred samples each of lane-changing intent and lane keeping behaviours are selected for use as training samples. Neural network training is conducted using the MATLAB software. The training parameter values used are shown in Table 4.

The weights and thresholds of the network can be modified via the training to minimize the network output error. The network's training error curve is shown in Fig. 14. After training the network for nine times, the training error converges to 0.00924, which is

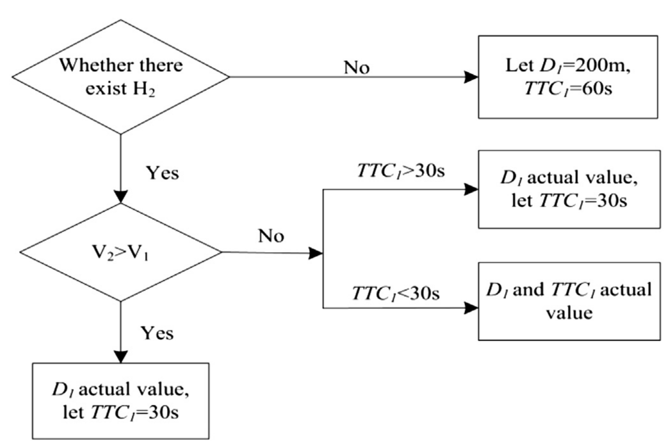

Fig. 13. Vacancy assignments for D_1 and TTC_1.

Table 4
Training parameter settings.

Training times	Training target	Learning rate
1000	0.01	0.1

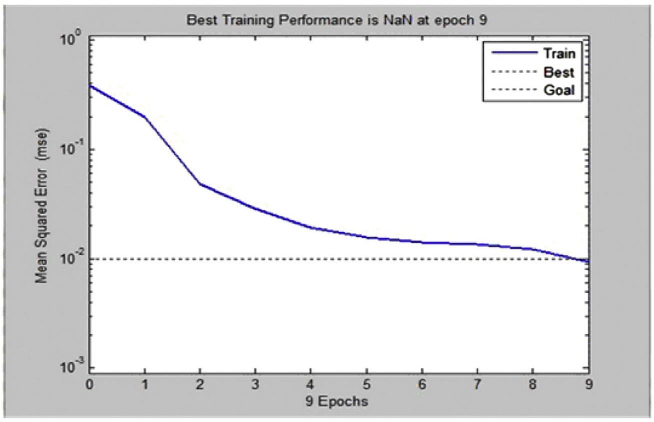

Fig. 14. Training error curve of the network.

smaller than the training target of 0.01, indicating that the model achieves good classification performance.

6. Lane change prediction

After training the model and assessing the performance of the BP network with respect to the training samples, the remaining samples could be input into the BP model to predict lane-changing behaviour. Given the network outputs a value between 0 and 1, a threshold value must be determined to identify the sample properties. To avoid the blindness of choosing a random threshold value, in engineering practice ROC curves (receiver operator characteristic curves, which are obtained via series of threshold value, as shown in Fig. 15) usually are used to evaluate the classification effect of the prediction model. Generally, in engineering practice the acceptable FPR (False Positive Rate) is about 5%, and its corresponding critical value in the ROC curve is served as the threshold value to distinguish lane keeping and lane changing intent samples (Tao, 2011). And in our research, according to the input and output characteristics of all the samples, when FPR is 5%, its corresponding threshold value is 0.5. If $T(Z) \geq 0.5$, a driver is predicted to execute lane-changing behaviour, whereas if $T(Z) < 0.5$, a driver is predicted to exhibit lane keeping behaviour. By comparing the prediction results for each sample with its actual attribute, the prediction accuracy of the BP network model could be assessed.

To compare the effects of the different parameters on lane change prediction, various combinations of characteristic indexes are used as input vectors. Corresponding BP network models are then built based on the learning samples, and the prediction process is then conducted for the prediction samples. The prediction accuracy results are summarized shown in Table 5.

When the input vector contains only turn signals, the prediction accuracy is approximately 30.71%. While the standard deviation of the head rotation degree in the horizontal direction is added to the input vectors, the prediction accuracy increases to 70%, which indicates that information on drivers' head motion characteristics is essential to improving the prediction performance. When the input vectors contains all seven of the parameters, the prediction accuracy reaches 95.09%, which shows that the BP model possesses the characteristics of applicability and reliability in predicting drivers' lane-changing behaviour.

In addition to the model's prediction reliability, its prediction accuracy with respect to time is also considered in the evaluation of the performance of the prediction model. For input vectors containing all seven of the parameters, the prediction performance trends for the lane changing intent samples are shown in Fig. 16. Five seconds before changing lanes, the prediction accuracy is approximately 3.88%. It rapidly improves to 85.44% till 1.5 s before changing lanes and finally reaches 95.63% in the moment of lane change initiation. Fig. 16 also shows the change in the turn signal use rate in time series. The results reveal that the model's prediction accuracy is substantially higher than that of the turn signal use rate at any time, which indicates that the model developed in this study possesses not only prediction accuracy advantages but also distinct time series characteristics.

7. Discussion and conclusion

The main objective of this study is to develop a new method for predicting lane-changing behaviour in advance of drivers'

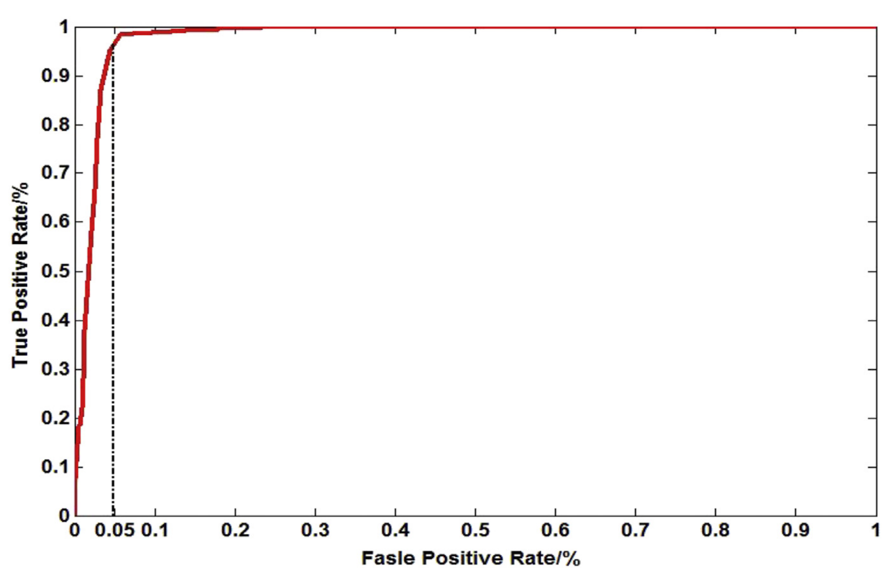

Fig. 15. ROC curve of the prediction.

Table 5
Prediction results for various combinations of input vectors.

Serial number	Vector element	Accuracy rate
1	[TS]	30.71%
2	[TS, θ]	70.02%
3	[TS, TTC_2, D_2, θ]	71.99%
4	[V, TS, D_1, θ]	80.59%
5	[V, TS, TTC_1, TTC_2]	86.24%
6	[V, TS, TTC_1, D_1, TTC_2, D_2]	88.70%
7	[V, TS, TTC_1, θ]	89.93%
8	[V, TS, D_1, TTC_1, θ]	90.66%
9	[V, TS, TTC_1, TTC_2, θ]	92.38%
10	[V, TS, TTC_1, D_1, TTC_2, D_2, θ]	95.09%

executing lane-change manoeuvres. Based on the results of on-road naturalistic driving tests, driving behaviour characteristics during lane changing and lane keeping are extracted via offline data analysis. A comprehensive prediction index system is constructed based on drivers' head movement characteristics, vehicle operation behaviour, vehicle motion states, and driving conditions. A neural network model is then built to predict lane-change behaviour. The results show that the prediction accuracy of the model reaches 85.44% till 1.5 s before changing lanes and increases to 95.63% in the moment of lane change initiation. These results indicate that the model achieves good prediction performance and has good time series characteristics.

Determination of the lane-change-intent time window is a key procedure to the development of the lane-change prediction model. In this study, the lane changing intent time window is found to be five seconds long, based on analysis of the drivers' visual search characteristics. Huo (2010) suggested a six-second length for a driver's lane-changing time window, based on examination of experimental videos. Obviously, this approach for determining the length of the lane-changing intent time window is more subjective than the method used in our research. However, given lane changing intent time window is determined mostly depend on the visual characteristics of the side/rearview mirrors, it has certain limitation. Among 406 lane changing intent samples, 11 samples show no glances to side/rearview mirrors. Aim at this, in our future research we need to propose a new calculation method of intent window length on the condition that drivers show no glances to side/rearview mirrors. Moreover, the five-second length of the time window determined in this study is based on the driving behaviour characteristics of just 16 subjects. For different drivers, the length of the lane-change-intent time window may be different.

Information on visual search characteristics during the intent stage is found to be essential to predicting drivers' lane-changing behaviour. In this study, we used the faceLAB 5 system to track drivers' eye and head movements. At the time of the study, we had only one set of faceLAB 5 cameras on our collection platform. Due to of the restricted tracking range of the gaze angle in the horizontal direction, the system usually failed to track drivers' visual information when drivers' fixation points dwelled at the objects in the far right. Therefore, only leftward lane changes were used as lane changing intent sample data. In the near future, we may expand the tracking range by installing another set of faceLAB 5 cameras. This would permit analysis of driving behaviours during lane changes to the right, which may improve the applicability of the prediction model.

When drivers intend to change lanes, they are found to pay more attention to side mirrors and the dashboard than when they intend to remain in their current lanes. These findings are consistent with those of a previous study (Lethaus and Rataj, 2007). To improve the performance of an existing lane-changing assistance system based on drivers' visual search characteristics, an enormous amount of work has been done to determine how to predict drivers' lane-changing intentions (Henning et al., 2007; Peng et al., 2013a,b). However, a driver intending to change lanes does not necessarily mean that a lane change will be executed. During actual driving, the "intent revocation" phenomenon occurs often: a driver intends to change lanes but finds that the conditions of the surrounding environment do not meet the requirements for lane-changing behaviour. An example of such a condition would be a fast-approaching car in the target lane. Intent revocation occurs

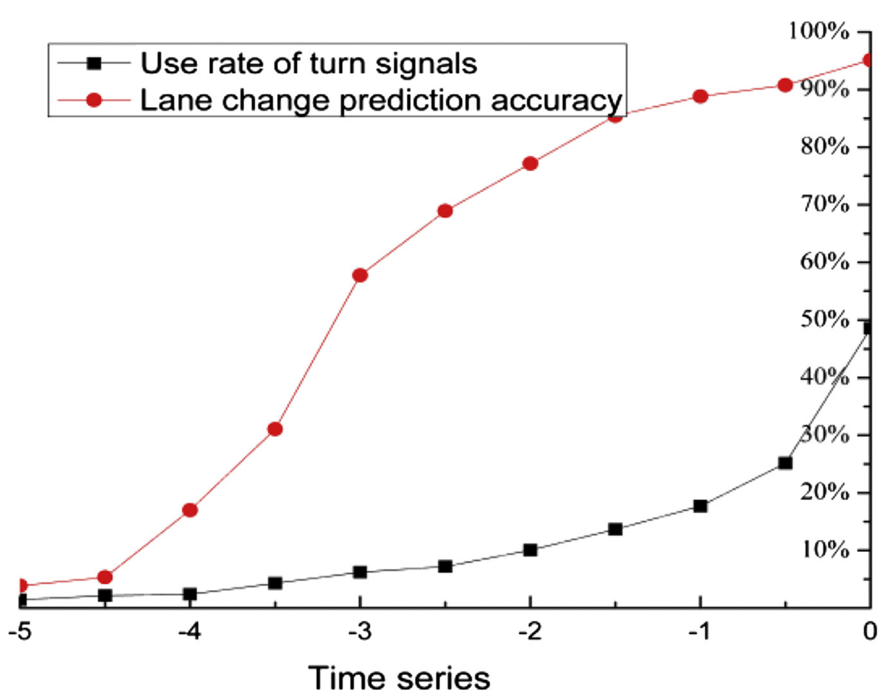

Fig. 16. Prediction accuracy of changing trends in the time series.

when the driver abandons the idea of changing lanes, usually for safety reasons. The prevalence of the intent revocation phenomenon makes lane change prediction more meaningful and more valuable than intent identification.

The prediction index system developed in this study includes parameters for head movements, use of turn signals, car speed, and the relative motions parameters between the object car and the conflict cars. Essentially, the composition of the characteristic index system reflects the fact that lane change prediction can be divided into two processes, namely, lane-changing intent identification and feasibility recognition. The head rotation degree in the horizontal direction was used to identify a driver's lane-changing intent, and the feasibility of changing lanes can be determined based on learning from a large number of samples. That is, if lane-changing intent is generated and the driving environment meets the space and time conditions, a lane change may occur soon. The results shown in Fig. 16 indicate that the prediction accuracy of the model developed in this study reaches 85.54% till 1.5 s before changing lanes. If we define 85% as the threshold of high accuracy, we may consider the BP neural network model developed in this study to be able to accurately predict a lane change 1.5 s before changing lanes, which is of great importance in ensuring driving safety. Existing lane-changing assistance systems rely on turn signal use as the indicator of a driver's likelihood of changing lanes. However, because of drivers' irregular driving behaviour, such assistance systems often fail to achieve acceptable prediction performance. The results of this study indicate that use of the model developed to predict drivers' lane-changing behaviour can dramatically improve the performance of a lane-changing assistance system.

There still are a few aspects of our work that need to be improved in future research. In this study, construction of the characteristic index system and the application of the prediction model are based on offline data analysis. To perform online prediction of lane-changing behaviour, input vectors must be adjusted according to the parameters' characteristics over time, and new theoretical approaches are needed for online prediction purposes. In addition, in this study, during the model training process, samples from different subjects were combined together as the training samples, which may have masked differences in driving behaviour characteristics among the subjects. On the condition that the numbers of samples are sufficient, a future study will focus on building prediction models based on individual drivers' driving behaviours to improve the reliability of the prediction results.

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