Real-Time Overtaking Manoeuvre Detection with Random Forest

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I. INTRODUCTION

Advanced Driver Assistance Systems (ADASs) have been in great demand in recent years for enhancing drivers' safety greatly. A recent estimation study of ADAS declares that a Lateral Guidance System can potentially prevent 7.3% of all car accidents [1]. To assist drivers better, more information about driver manoeuvres is needed to be understood, especially when drivers are in a dangerous situation such as overtaking. Researchers intent to detect drivers' lane-changing manoeuvres are trying several classifiers, including Hidden Markov Model [2], Model Tracking Method [3], Support Vector Machines [4], Bayesian Learning [5] etc. Although the classifiers above can detect lane-changing manoeuvres after the onset of steering, which is always viewed as the start moment of lane-changing [6], an optimised feature set that can validly improve the detection rate is unclear. The purpose of this paper is to propose a method to select an optimised feature set from drivers' overtaking manoeuvres as well as design a classifier based on the selected feature set.

II. METHODS

This overtake experiment was carried out on a six-degree-of-freedom driving simulator (Fig.1) and 17 experienced male drivers between 20-40 years were recruited. Subjects had to overtake the leading car in a two-lane highway scenery, after the overtaking instruction was given.

Fig.1 The Driving Simulator

Modelling

Ninety thousand training samples were selected from 132 overtaking manoeuvres, including lane-keeping (LK), left lane-changing (LLC) and right lane-changing (RLC). The sample window is defined as 1.0 seconds in this paper. Seven statistical characteristics (mean value, standard deviation, the 25th percentile, 50th percentile, 75th percentile and the interquartile range) were calculated for each vehicle operating parameter, counting to 102 features with 17 parameters (TABLE I).

TABLE I
PARAMETERS FROM VEHICLE OPERATING DATA

Parameter	Parameter	Parameter	Parameter
Lane departure(m)	*Longitudinal speed(m/s)*	*Steering angle (o)*	*Throttle(-)*
Course angle(°)	*Following distance(m)*	*Acceleration(m/s^2)*	*Brake(MPa)*
Yaw velocity(°/s)	*Lateral acceleration(m/s^2)*	*Steering torque(N*m)*	*Speed(m/s)*
Lateral speed(m/s)	*Longitudinal acceleration(m/s^2)*	*Time to collision(s)*	*Relative speed(m/s)*
	Steering angular velocity(°/s)		

A Sequential Backward Selection (SBS) method based on Random forest (RF) was used to select the optimised features and design the final RF model, following these steps:

1) Bootstrapping k training samples from all samples $(k \le 90000)$ randomly to build 500 trees. The samples excluded from bootstrapping formed the out-of-bag dataset.
2) For each tree, selecting m features randomly $(m \le 102)$, calculating the features information by GINI coefficient of each node, the minimum GINI coefficient will define the category of this node .

$$GINI = \sum_{i=1}^{k} p_i^j (1-p_i^j), \quad i=-1,0,1 \tag{1}$$

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where p_i^j is the proportion of category i in feature j. $i=-1$ means RLC, $i=0$ means LK and $i=1$ means LLC.

3) Calculating the out-of-bag data in the root node's GINI coefficient and output, and the category where the GINI coefficient reaches the threshold of this node is the output of this tree. The largest votes of the category in 500 trees will be the final output.
4) Comparing the labels and the outputs of the out-of-bag dataset, calculating the weight of each feature:

$$IM_i = \frac{1}{k}\sum_{i=1}^{k}(acc_i - acc_i') \tag{2}$$

where acc_i is the accuracy of feature i, acc_i' is the accuracy of feature i after disturbing and IM_i is the importance of feature i.

5) Deleting the least important feature from the feature set judging by the weight, rebuilding the RF model.
6) Each RF model goes through the 10-fold cross validation and the feature set with the highest result is viewed as the optimised feature set.

III. INITIAL FINDINGS

Shown in Fig. 2 is the 10-fold cross validation result of each RF model in different feature dimensions. Accuracy will reach its maximum in a feature set of 73 feature dimensions. Testing results of 45 overtaking manoeuvres from 10 drivers selected randomly are shown in Table 2, where LLC and RLC achieved good detection accuracy while LK did not. A continuous testing result is shown in Fig 3, in which we can see a great continuous detection result of overtaking manoeuvres, and discover that the wrong detection of LK before RLC is the main reason leading to the low detection accuracy of LK in all. This algorithm can detect the onset of an overtaking manoeuvre 0.40s after the driver start to steer. On-line leaning was applied based on the off-line RF model, and the mean detection result proved great in the test of 6 overtaking manoeuvres from one driver, who spent little time on the phase before RLC (shown in Table 3).

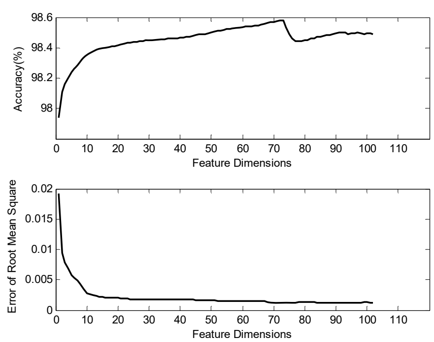

Fig. 2 10-Fold Cross Validation of all RF models in different feature dimensions

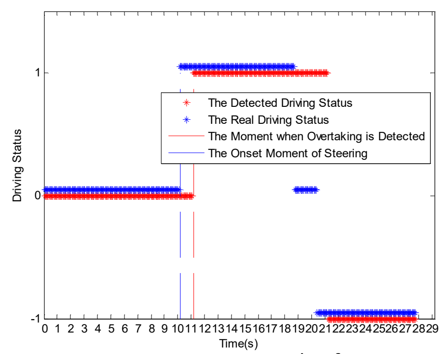

Fig.3 Continuous testing result of a test sample

In Fig.3, when the driving status output is 0, it means the vehicle is in LK phase, while 1 means LLC and -1 means RLC.

TABLE 2

MEAN DETECTION ACCURACY OF 45 OVERTAKING MANOEUVEES

	Recognised as LK	Recognised as LLC	Recognised as RLC
LK	**67.08%**	29.91%	9.01%
LLC	7.45%	**92.01%**	0.54%
RLC	0.00%	4.81%	**95.19%**

TABLE 3

MEAN DETECTION ACCURACY OF 6 OVERTAKING MANOEUVRES FOR ON-LINE LEARNING AND OFF-LINE LEARNING

	LK	LLC	RLC
Off-line learning	91.12%	90.76%	90.98%
On-line learning	91.12%	91.47%	92.10%

IV. DISCUSSION

From the initial findings above, a better feature set can be selected based on SBS . The LLC and RLC can be validly detected with the RF model. LK gets the accuracy below 70%, which may be due to the the wrong detection of LK before the RLC phase as shown in Fig.3. The main reason may be in the exclusion of this phase samples in the modelling training samples or the close similarity of the features of this phase to LLC or RLC, as the driver is preparing to return to the initial lane and behave like in lane changing. Online learning based on the off-line RF model can improve the detection accuracy, which maybe a way to eliminate the difference between drivers and improve the detection accuracy for the targeted driver, but how to overcome the great time cost as traning samples become more and more within the RF model is a problem to be solved .

V. References

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