Journal of Zhejiang University-SCIENCE C (Computers & Electronics)
ISSN 1869-1951 (Print); ISSN 1869-196X (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

Driving intention recognition and behaviour prediction based on a double-layer hidden Markov model*

Lei HE†, Chang-fu ZONG†‡, Chang WANG
(*State Key Laboratory of Automotive Simulation and Control, Jilin University, Changchun 130025, China*)
†E-mail: jlu_helei@126.com; cfzong@yahoo.com.cn

Received July 17, 2011; Revision accepted Dec. 7, 2011; Crosschecked Feb. 9, 2012

Abstract: We propose a model structure with a double-layer hidden Markov model (HMM) to recognise driving intention and predict driving behaviour. The upper-layer multi-dimensional discrete HMM (MDHMM) in the double-layer HMM represents driving intention in a combined working case, constructed according to the driving behaviours in certain single working cases in the lower-layer multi-dimensional Gaussian HMM (MGHMM). The driving behaviours are recognised by manoeuvring the signals of the driver and vehicle state information, and the recognised results are sent to the upper-layer HMM to recognise driving intentions. Also, driving behaviours in the near future are predicted using the likelihood-maximum method. A real-time driving simulator test on the combined working cases showed that the double-layer HMM can recognise driving intention and predict driving behaviour accurately and efficiently. As a result, the model provides the basis for pre-warning and intervention of danger and improving comfort performance.

Key words: Vehicle engineering, Driving intention recognition, Driving behaviour prediction, Driver model, Double-layer hidden Markov model (HMM)
doi:10.1631/jzus.C11a0195 **Document code:** A **CLC number:** TP391; U463.6

1 Introduction

This study aims to develop a method for recognising driving intention and predicting driving behaviour. More efforts are under way to research and develop advanced vehicle chassis electronic control systems, such as the X-by-wire system, direct yaw moment control, and emergency brake assist, which make driving safer and more comfortable. However, all of them rely heavily on driving intention recognition and driving behaviour prediction, in order to choose a suitable control strategy to assist and/or warn the driver. Alongside the aforementioned circumstances, driving intention recognition and behaviour prediction have attracted much attention, and in consideration of the sequential characteristic of driving behaviour, the hidden Markov model (HMM), which is suitable for dynamic time series modelling, has been widely used in the recognition and prediction of driver behaviour. Kishimoto and Oguri (2008) focused on the prediction of the future stop probability through a simple dynamic Bayesian network, vehicle speed, and pedal strokes of the acceleration and brake pedals. Pentland and Liu (1999) described driver behaviour as a dynamic model sequenced with a Markov network and used dynamic Markov models to recognise and predict human behaviours. Takano *et al.* (2008) presented a hierarchical model with the HMMs for both recognition and generation of the driving patterns about steering. Raksincharoensak *et al.* (2008) recognised driver steering behaviours with the application of the HMM, to achieve direct yaw moment control. Overall, the present research on recognition and prediction is about a single working case, in which only steering or accelerator/brake

‡ Corresponding author
* Project (Nos. 50775096 and 51075176) supported by the National Natural Science Foundation of China

pedal behaviour is considered. Few investigations have addressed online long-term driving intention recognition in a combined working case of steering, braking, and acceleration, by manoeuvring only signals of the driver and vehicle state information, and prediction of driving behaviour in the next time step.

This study establishes a double-layer HMM using driving behaviour data and vehicle state information (Rabiner, 1989), where the multi-dimensional Gaussian HMMs (MGHMMs) in the lower layer represent various short-term driving behaviours in a single working case. The multi-dimensional discrete HMMs (MDHMMs) in the upper layer indicate long-term driving intention in a combined working case, in which both steering and accelerator/brake pedal behaviour are considered. When all the parameters of the HMMs in each layer have been optimised, the short-term driving behaviour and long-term driving intention are recognised online layer by layer using LabVIEW (Beyon, 2000). In addition, we propose a method for driving behaviour prediction based on the established double-layer HMMs. Accuracy and efficiency are verified by an online driving simulator test, which creates the basis for control mode transitions and accident warning.

2 Double-layer hidden Markov model

In the case of driving in a specific environment, the driver schedules the task in terms of determining when and which manoeuvres are most appropriate (Xi and Levinson, 2006). That is, long-term driving intention is divided into several long chains of simpler short-term driving behaviour which take place in a particular order, and each chain relates only to one type of driving behaviour such as driver's steering behaviour. Then, the driver executes the driving behaviour arranged before; that is, the accelerator/brake pedal and steering wheel are moved to a position at an appropriate rate, for example, releasing the accelerator pedal quickly in a single working case. Considering that HMM is based on module design philosophy and statistical theory, and is suitable for dynamic time series modelling (Rabiner, 1989; Oliver *et al*., 2004; Cappé *et al*., 2005), we develop a double-layer HMM to model driving behaviour and driving intention in the lower and upper layers, respectively. The lower layer of the architecture is connected to the upper layer via its inferential results. The structure of a double-layer HMM is shown in Fig. 1.

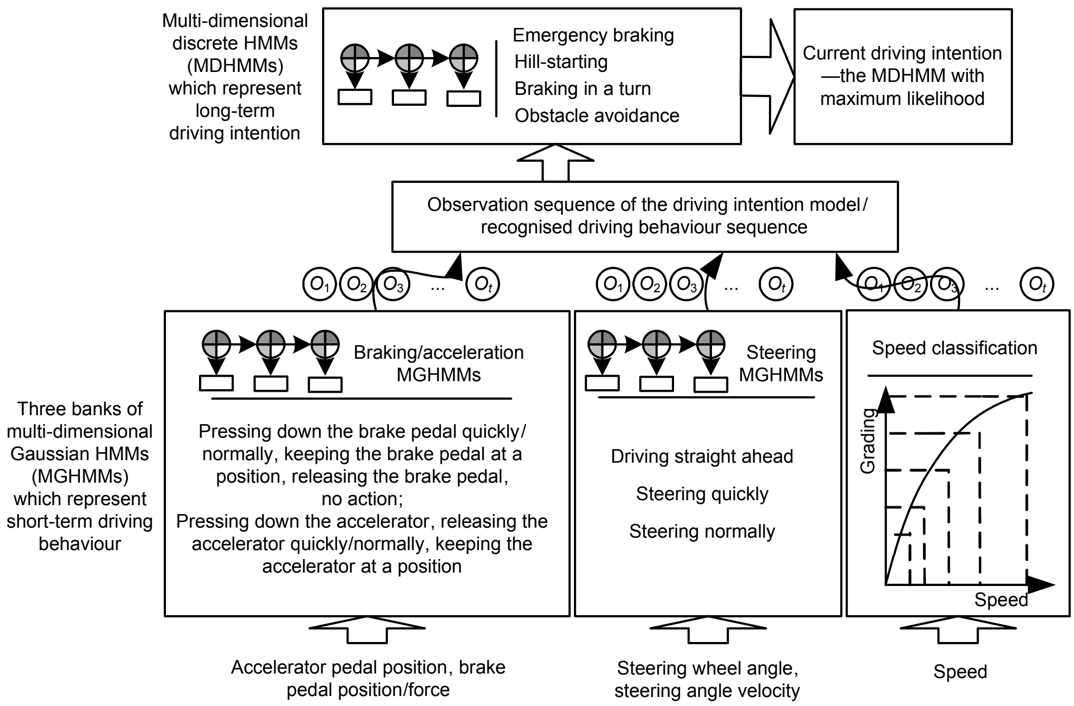

Fig. 1 Double-layer hidden Markov model (HMM) structure

In the lower layer, there are two banks of MGHMMs for recognising the steering and braking/acceleration driving behaviours and a bank for speed classification. All of the models are executed simultaneously with relevant manoeuvring signals of the driver and vehicle speed after data processing. At each instant, the model with the highest likelihood in each model bank is selected as the current short-term driving behaviour. After a while, three sequences of driving behaviours of steering, braking/acceleration, and speed grading are localized by selection in this way. The inferential results from the lower layer (i.e., three sequences of driving behaviours) are passed to the upper layer. The models at this level are also discriminative HMMs, with one MDHMM per driving intention in a combined working case. Likelihoods that each MDHMM occurs with the inferential results are calculated, and the one with the maximum likelihood is chosen as the current driving intention. These will be explained in detail in the following.

2.1 Hidden Markov model (HMM)

An HMM can be considered as a simple dynamic Bayesian network with two concurrent stochastic processes, a Markov process and a general stochastic process. That is, in an HMM, the state is not directly visible, but the output, dependent on the state, is visible. Each state has a probability distribution over the possible observations by the general stochastic process, and the probability of transferring state can be represented through the Markov process. Therefore, the observation sequence generated by an HMM gives some information about the sequence of states and the model (Rabiner, 1989). In our application, we build MGHMM for each short-term driving behaviour and MDHMM for each long-term driving intention. The hidden states in the model are concerned in a particular sub-operation at a different level.

2.2 Multi-dimensional Gaussian HMM for driving behaviour

By analysis and summarization of the driving process, it is known that the driver operates the brake/accelerator pedal and steering wheel in parallel. In addition, braking and acceleration behaviours are independent of each other and occur one after another. Thus, driving behaviour may be divided into two sharply different categories, steering manoeuvre and braking/acceleration manoeuvre (which combines acceleration behaviour with braking behaviour). These two categories can also be divided into several simpler short-term driving behaviours which take place in a particular order. Thus, we train nine braking/acceleration driving behaviour HMMs for all the short-term braking/acceleration manoeuvres, which are pressing down the brake pedal quickly, pressing down the brake pedal normally, keeping the brake pedal at a fixed position, releasing the brake pedal, no action, pressing down the accelerator pedal, releasing the accelerator pedal normally, releasing the accelerator pedal quickly, and keeping the accelerator pedal at a fixed position, with corresponding data for certain manoeuvres. Three steering driving behaviour HMMs, i.e., driving straight ahead, steering quickly, and steering normally, are trained for all the short-term steering manoeuvres.

The observation sequences of driving behaviour HMMs are manoeuvring signals of the driver and vehicle speed. It is clear that the signals are continuous, in order to prevent degradation associated with signal quantisation, and driving behaviour MGHMMs are built using MGHMM theory (Rabiner, 1989).

As is known, when establishing the HMM-based model, parameter determination is the foremost task. On modelling braking/acceleration driving behaviour, sensor signals including accelerator pedal position, brake pedal position, and brake pedal force are extracted to train braking/acceleration driving behaviour MGHMMs. In these braking/acceleration MGHMMs, observation sequences can be represented by

$$O_{\mathrm{G}}(t)=\{a(t),\ b(t),\ c(t)\},\tag{1}$$

where $a(t)$ represents the accelerator pedal position, $b(t)$ the brake pedal position, and $c(t)$ the brake pedal force (Meng *et al*., 2006).

All the braking/acceleration driving behaviour MGHMMs are trained independently of each other using the Baum-Welch algorithm which is an 'iterative update' algorithm to construct an HMM fitting given observation sequences (Rabiner, 1989). Thus, the parameters of a certain short-term driving behaviour model are optimised gradually, to make the probability of adopting the driving behaviour reach 100%, for given sensor data. Similarly, MGHMMs for three steering driving behaviours are built for all steering manoeuvres with particular sensor data, including the steering wheel angle and steering angle velocity.

Then, the criterion for speed classification is designed. Speed is numbered based on its value. That is, if speed is in the range of 80–90 km/h, then the speed rank is 8. Furthermore, as the observation sequences of HMM cannot be 0, the speed in the range of 0–10 km/h should be represented by a special number.

Thus, there are three modules in the lower layer for recognising short-term driving behaviours and speed classification. When new sensor data is sent to a corresponding module after sorting by driving behaviour, the likelihoods of all the MGHMMs in each bank are calculated using the forward-backward algorithm (Rabiner, 1989), which shows the computation of the probability that the observed sequence is produced by the model. Finally, the model with the maximum likelihood in each bank is selected as the recognised driving behaviour. Thus, current braking/acceleration driving behaviour, steering driving behaviour, and speed rank are determined.

Long sensor data acquired from a certain combined working case is sorted into three groups according to a single working case. Then each group is divided into several short segments; each segment is 0.08 s long. The data segments occurring at the same time are sent to three corresponding modules and determine current driving behaviours, as shown in Fig. 1. In this way, three chains of recognition results can be obtained through segment by segment recognition.

2.3 Multi-dimensional discrete HMM for driving intention

In certain combined working cases, drivers have specific driving behaviour sequences, e.g., braking in a turn, in which driving behaviours take place in the following order: (1) only steering, (2) steering and releasing the accelerator pedal, (3) steering and no action on the brake/accelerator pedal, (4) steering and pressing the brake pedal down.

Thus, based on the fact that the driver makes preferred behaviour sequences under certain driving intentions, we take inferential driving behaviour chains as the observation sequences of the MDHMMs in the upper layer, which are built for driving intention including emergency braking, obstacle avoidance, Hill-starting, and braking in a turn. In the driving intention MDHMM, the observation sequence can be represented by

$$O_{\mathrm{D}}(t)=\{x(t), y(t), z(t)\}, \tag{2}$$

where $x(t)$ represents the symbol string for recognised braking/acceleration driving behaviours, $y(t)$ the symbol string for recognised steering driving behaviours, and $z(t)$ the speed grading. Then, the iterative formulas for forward variable $\alpha_t(i)$ and backward variable $\beta_t(i)$ in HMM theory can be revised as

$$\alpha_{t+1}(j)=\left(\sum_{i=1}^{N}\alpha_t(i)a_{ij}\right)\prod_{l=1}^{3}b_j(O_{\mathrm{D}(t+1)}(l)), \tag{3}$$

$$\beta_t(i)=\left(\sum_{j=1}^{N}\beta_{t+1}(j)a_{ij}\right)\prod_{l=1}^{3}b_i(O_{\mathrm{D}t}(l)), \tag{4}$$

where $\alpha_{t+1}(j)$ is the probability of the partial observation sequence $O_1O_2\ldots O_tO_{t+1}$ at state S_j at time $t+1$, $\beta_t(i)$ is the probability of the partial observation sequence from $t+1$ to the end, given state S_i at time t, $\alpha_{t+1}(j)$ and $\beta_t(i)$ can be solved inductively, a_{ij} is the state transition probability distribution from S_i to S_j, and $b_i(O_{\mathrm{D}t}(l))$ is the observation symbol probability distribution of the occurrence of observable value $O_{\mathrm{D}t}(l)$, given state S_i at time t (Rabiner, 1989).

The re-estimation formulas for the initial state distribution $\boldsymbol{\Pi}$ and the state transition probability distribution $\boldsymbol{A}$ are the same as before. Nevertheless, the re-estimation formula for the observation symbol probability distribution is changed to

$$\bar{b}_j^{(l)}(k)=\mathrm{count}(k^{(l)}\mid j)/\mathrm{count}(j), \tag{5}$$

where $\mathrm{count}(k^{(l)}|j)$ represents the expected amount of occurrences of observable manoeuvring behaviour k at state j, and the observable manoeuvring behaviour k belongs to one driving behaviour set l (l=1, 2, 3).

Thus, the MDHMM can be described as

$$\lambda_{\mathrm{D}}=(\boldsymbol{\Pi}_2,\boldsymbol{A}_2,\boldsymbol{B}_1,\boldsymbol{B}_2,\boldsymbol{B}_3), \tag{6}$$

where $\boldsymbol{B}_1$, $\boldsymbol{B}_2$, and $\boldsymbol{B}_3$ are the observation symbol probability distributions for the three observation sequences of the upper-layer MDHMM. We revise the Baum-Welch algorithm using Eqs. (3)–(5) and optimise four MDHMMs using the revised Baum-Welch algorithm.

Fig. 2 summarizes the training process of double-layer HMM for a certain combined working case.

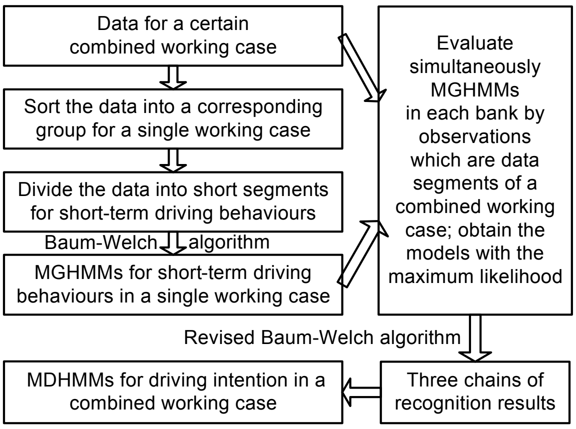

Fig. 2 The training process of double-layer hidden Markov model (HMM)

Take the HMMs for 'releasing the accelerator pedal quickly' and 'braking in a turn' as the examples. MGHMM is chosen to model the short-term driving behaviour 'releasing the accelerator pedal quickly', and the numbers of states and mixtures determined are both three. Thus, the parameters of the MGHMM include initial state distribution $\boldsymbol{\Pi}_1$ (3×1), state transition probability distribution $\boldsymbol{A}_1$ (3×3), mixture coefficient matrix $\boldsymbol{C}$ (3×3), mean matrix $\boldsymbol{\mu}$ (3×3×3), and covariance matrix $\boldsymbol{\sigma}$ (3×3×3×3). Similarly, the long-term driving intention 'braking in a turn' is built by MDHMM. As previously mentioned, there are five parameters: initial state distribution $\boldsymbol{\Pi}_2$ (3×1), state transition probability distribution $\boldsymbol{A}_2$ (3×3), and three observation symbol probability distributions $\boldsymbol{B}_1$ (3×8), $\boldsymbol{B}_2$ (3×3), and $\boldsymbol{B}_3$ (3×2). The parameters of the MGHMM for the short-term driving behaviour 'releasing the accelerator pedal quickly' are shown as follows:

$$\boldsymbol{\Pi}_1=\begin{bmatrix}0.7301\\0.0007\\0.2692\end{bmatrix},\ \boldsymbol{A}_1=\begin{bmatrix}0.9424&0.0000&0.0576\\0.0091&0.9656&0.0252\\0.0492&0.0211&0.9297\end{bmatrix},$$

$$\boldsymbol{C}=\begin{bmatrix}0.6983&0.1270&0.1747\\0.2518&0.2713&0.4770\\0.0564&0.4382&0.5054\end{bmatrix},$$

$$\boldsymbol{\mu}(:,:,1)=1\times10^3\times\begin{bmatrix}-0.3146&-1.3301&-0.8815\\0.0005&0.0023&0.0025\\0.0030&0.0017&0.0024\end{bmatrix},$$

$$\boldsymbol{\sigma}(:,:,1,1)=1\times10^4\times\begin{bmatrix}2.6182&-0.0127&-0.0037\\-0.0127&0.0004&0.0000\\-0.0037&0.0000&0.0001\end{bmatrix}.$$

The parameters of the MDHMM for the long-term driving intention 'braking in a turn' are shown as follows:

$$\boldsymbol{\Pi}_2=\begin{bmatrix}0.9830\\0.0119\\0.0051\end{bmatrix},\ \boldsymbol{A}_2=\begin{bmatrix}0.9677&0.0320&0.0003\\0.9273&0.0712&0.0015\\0.9452&0.0326&0.0222\end{bmatrix},$$

$$\boldsymbol{B}_1=\begin{bmatrix}0.1407&0.1675&...&0.0012&0.3007\\0.0841&0.3007&...&0.0433&0.1341\\0.0003&0.0036&...&0.0003&0.0021\end{bmatrix}_{3\times8},$$

$$\boldsymbol{B}_2=\begin{bmatrix}0.0493&0.9403&0.0104\\0.0066&0.9919&0.0015\\0.8659&0.1326&0.0015\end{bmatrix},$$

$$\boldsymbol{B}_3=\begin{bmatrix}0.0585&0.9415\\0.0452&0.9548\\0.0008&0.9992\end{bmatrix}.$$

According to the modelling concept of 'double-layer HMM', short-term driving behaviour in the lower layer can be recognised synchronously in a modular approach, which could raise the calculating efficiency. Also, the double-layer HMM enables the linking of short-term driving behaviours to long-term driving behaviours, which is arranged by certain driving intention in a certain combined working case. More importantly, when new data needs to be considered, we model MDHMMs in the upper layer and need only to consider the new data as a new module in the lower layer, and then take corresponding recognition results as a new dimension of the observation sequences of the upper-layer MDHMM (instead of retraining all the MGHMMs in the lower layer by which all the sensor data is considered), thus reducing the workload for training.

3 Modelling and statistical analysis

Relying on the stationary, real environment driving simulator (Guo *et al.*, 1999), 10 subjects (five males and five females) who have driving license participated in the experiment (Kuge *et al.*, 2000). The subjects were aged 20–60. Ten runs were executed for each combined working case per subject. Driving behaviours were measured as follows:

1. Emergency braking: While a subject stayed in one lane on a straight segment, one auxiliary experimenter shouted “stop”, without any prior warning, which meant a danger ahead. The subject was instructed to brake immediately in the same lane (security, single working case).

2. Hill-start: For a vehicle equipped with a Hill-start assist system (HAS) parking on the slope, the subject should take the following steps to start the Hill-start assist function (Ge, 2006): (1) press down the brake pedal rapidly and effectively, (2) release the brake pedal quickly, (3) move the foot to the accelerator pedal, and (4) step on the accelerator pedal. After these, release the hand brake and the vehicle will be able to start smoothly. The vehicle should stay in the same lane throughout the process (comfort, single working case).

3. Brake in a turn: While a subject drove round a curve, the auxiliary experimenter shouted “stop”, as described above. The subject was instructed to brake immediately but follow the lane (security and comfort, combined working case).

4. Obstacle avoidance: The subject drove through the test track designed based on ISO 3888-2 (security, single working case).

The entire sensor data acquired in the experiment comprised the database for training. The data was prepared following the steps shown in Fig. 3.

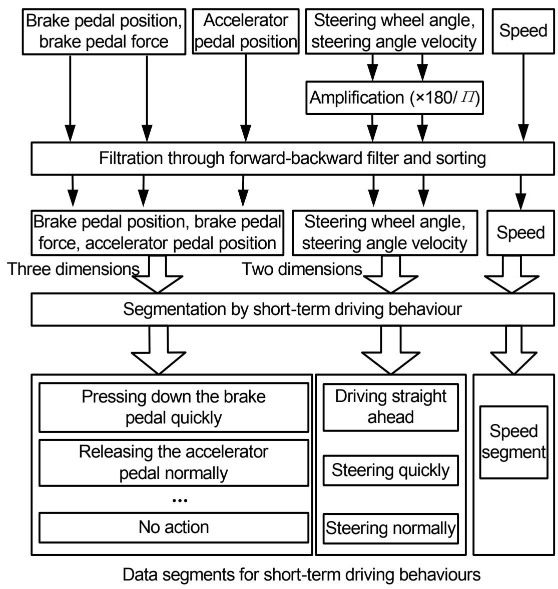

Fig. 3 The process of data preparation

Concerned about noise in sensor data and phase delay caused by filtration, a forward-backward filter, which is a combination of two filters having opposite filtering direction (Chen *et al.*, 2009), was used to eliminate the noise. After data processing including amplification and filtration, the data was processed by sorting into three groups for pedals, steering wheel, and speed, respectively; thus, three data sets were obtained. The data in each data set was cut into several segments, and the data segments were sorted according to the short-term driving behaviour to make one segment set concerned with only one short-term driving behaviour. For data segments relating to a certain driving behaviour, an abnormal data segment was discarded using the *t*-test method with the selected characteristic parameter (Wang, 2000). For example, the maximum accelerator pedal speed was chosen as the characteristic parameter for the driving behaviour ‘releasing the accelerator pedal quickly’. We then used the *K*-means method to set the limits for normal behaviour and emergency behaviour from the view of the driver, to verify the correctness of the recognition results. Fig. 4 shows the limits of sensor data for driving straight ahead, steering quickly, and steering normally.

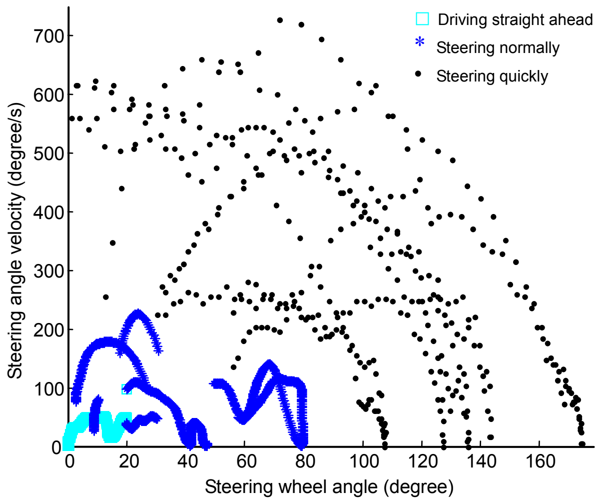

Fig. 4 The limits for driving straight ahead, steering quickly, and steering normally

4 Online recognition

After all MGHMMs and MDHMMs have been trained, all the optimised parameters were imported into the workspace of MATLAB. Then driving intention was recognised online, using also LabVIEW, a platform and development environment for a visual programming language developed by National Instruments (Beyon, 2000). Master/Slave design pattern in LabVIEW was used. In the Master loop, we collected six-channel sensor data from the driving simulator through dynamic link library technology. After amplification and filtration, the processed data was transferred to the Slave loop by queue structure. In the Slave loop, the data obtained from the Master loop was sorted and sent to the corresponding MGHMMs module. Through parallel computing, three chains of recognition results were obtained. Then, the current driving intention in a combined working case was recognised and shown with the recognition results received.

As HMM theory is based on the expectation maximization algorithm and driving intention MDHMM in the upper layer is not for all working cases, we set the limits of likelihoods for four driving intentions by means of many online tests (Rabiner, 1989). Just over the limit of likelihood, homologous driving intention in certain combined working cases can be confirmed.

After repeated experiments, a plot of mean accuracy rate of recognition versus time step was obtained (Fig. 5). A time step of 0.08 s was chosen to intercept sensor data and recognise driving behaviour in a single working case, which led to higher accuracy rate and met the requirement of real-time control as well. We had undertaken 630 braking/acceleration and 200 steering online recognitions for short-term driving behaviour. The accuracy rate obtained was around 99.85%.

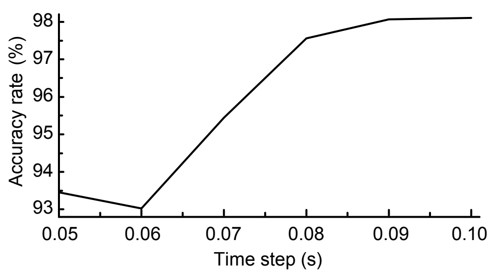

Fig. 5 Mean accuracy rate of recognition vs. time step

Table 1 shows some recognition results of steering driving behaviour, including four data segments from the testing data set of driving straight ahead, four from steering normally, and four from steering quickly. These 12 data segments were selected randomly and their log-likelihoods derived by all trained steering driving behaviour MGHMMs are given. The better did the data segment match the MGHMM, the larger was the log-likelihood (Rabiner, 1989).

Table 1 Recognition results of steering driving behaviour multi-dimensional Gaussian HMM

Data segment	Log-likelihood		
	DSA	SN	SQ
DSA 1	−939	−6462	−21 873
DSA 2	−1901	−5491	−8392
DSA 3	−1696	−14 763	−35 687
DSA 4	−574	−7770	−17 735
SN 1	−36 065	−1344	−7426
SN 2	−24 207	−949	−3020
SN 3	−11 775	−1400	−6372
SN 4	−19 719	−4521	−8335
SQ 1	−21 965	−5251	−1249
SQ 2	−28 062	−17 912	−1859
SQ 3	−74 251	−38 526	−1790
SQ 4	−68 607	−31 266	−1820

DSA: driving straight ahead; SN: steering normally; SQ: steering quickly. In each row, the maximum log-likelihood value is denoted, and the best recognitions are marked in gray

Fig. 6 shows the recognition results for one steering sensor data segment from the double-lane change working case. A high accuracy rate was obtained.

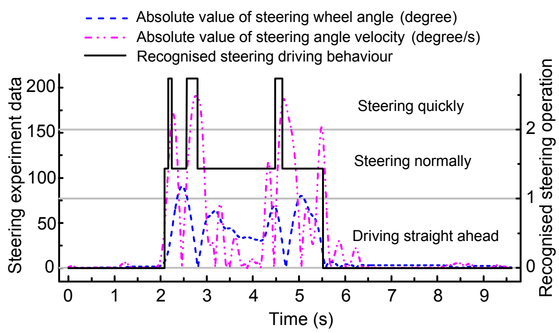

Fig. 6 Recognition results of steering multi-dimensional Gaussian HMM

Using the method described above, we recognised online long-term driving intention with six-channel sensor data. Fig. 7 shows the sensor data from one test of one project and the recognition results of driving behaviour and driving intention related to the sensor data. Fig. 7d presents the recognition results of short-term driving behaviour and observations of the driving intention model.

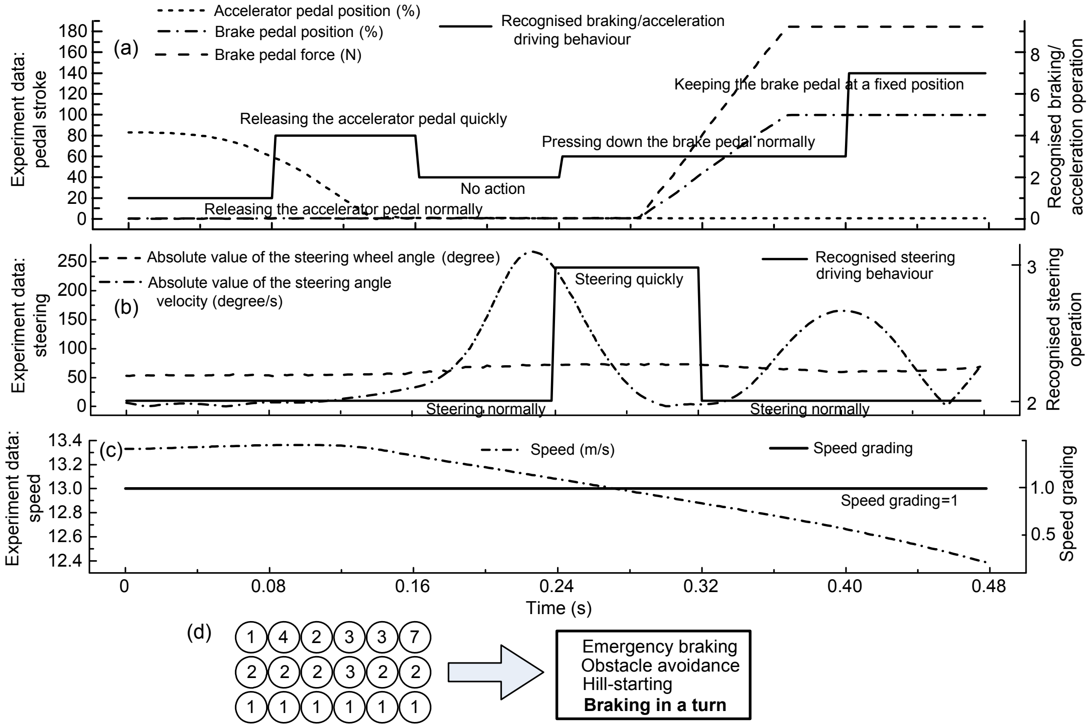

Fig. 7 Sensor data and recognition results of driving behaviour and driving intention

(a) Experiment data and recognised braking/acceleration driving behaviour; (b) Experiment data and recognised steering driving behaviour; (c) Experiment data and results of speed classification; (d) Recognition result of driving intention based on recognised driving behaviour

5 Prediction of driving behaviour

In the driving process, danger may exist due to previous wrong operations. For this reason, wrong driving behaviour recognition and potential hazard warning are very important for automobile safety, to remind the driver to take some remedial action or intervene directly in the driving task to avoid risk. For example, because of an emergency, the driver takes emergency braking during cornering at highway speed. In such a case, the vehicle weight will be redistributed and the probability of instability is increased. If prompted to slow down on corner entry and apply suitable brake pressure on certain wheels as the accelerator pedal is released quickly, to generate additional yaw moment, vehicle stability can be improved effectively.

According to the double-layer HMM structure and acquired steering wheel signals and accelerator pedal signals, it is learnt that the driver should release the accelerator pedal quickly in a turn. Thus, the system makes it clear that the brake pedal is pressed down quickly after a while and gives appropriate brake pressure on specified wheels to reduce brake clearance. Yet, this is a prediction for a behaviour that will occur after a long time and is used mainly for emergency situations. To predict an action in the near future (0.08 s in this study), verify the above predicted driving behaviour that will occur after a long time, and predict normal driving behaviour such as driving behaviour taken in the ‘braking in a turn’ combined working case, the algorithm for predicting driving behaviour in the near future is proposed as follows:

Step 1: The optimised parameters in the current combined working case are selected from the workspace, such as parameters of ‘braking in a turn’ MDHMM.

Step 2: Take the observation sequences of upper-layer MDHMM and add accordingly a set of observation symbols to the end of the original observation sequences of MDHMM. The added observation symbol set includes a symbol for recognised steering driving behaviour, a symbol for recognised braking/acceleration driving behaviour, and a symbol for speed grading (just like Fig. 7d). Therefore, a new observation sequence of upper-layer MDHMM can be obtained. One set of observation symbols represents one possibility. Consider all the driving behaviours that may occur. Driving straight ahead, steering quickly, and steering normally can all be the next steering driving behaviour. We can add observation symbol 1, 2, or 3 each time to the original steering observation sequences of MDHMM. Several new observation sequences of upper-layer MDHMM can be obtained.

Step 3: Likelihoods of all the new observation sequences obtained in step 2 are computed using the forward-backward algorithm.

Step 4: The observation sequence with the maximum likelihood is chosen. The set of observation symbols added to the original observation sequence is the result for behaviour prediction in a certain combined working case.

In line with the driving process of Hill-starting (Ge, 2006), the braking/acceleration driving behaviour and steering driving behaviour in the near future of the Hill-starting combined working case can be predicted using the method mentioned above. Fig. 8 shows the prediction results. The method for driving intention recognition and manoeuvring behaviour

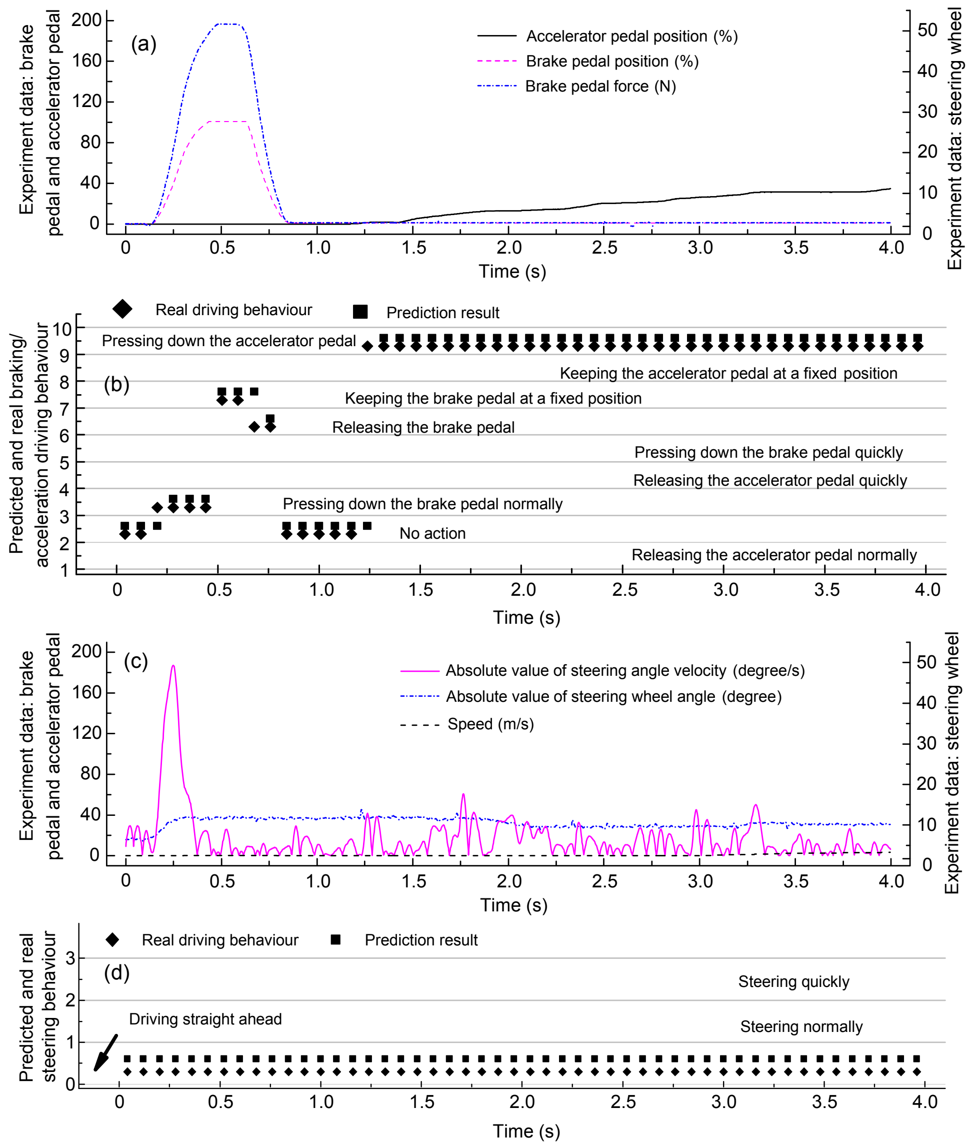

Fig. 8 The sensor data and the predicted braking/acceleration and steering driving behaviours
(a) Brake pedal and accelerator pedal sensor data; (b) Predicted and real braking/acceleration driving behaviour; (c) Steering angle and speed sensor data; (d) Predicted and real steering driving behaviour. Six-channel sensor data in (a) and (c) is from one test of one project

prediction performs well for accuracy, with only manoeuvring signals of the driver and vehicle state. Yet, under some emergency situations, we still need camera equipment and other signals to obtain driver expressions and predict driving behaviour.

The system using our proposed method achieves control mode smooth transitions between automated and manual operations of semi-automatic vehicles by predicting driving behaviour. This may give new drivers some suggestions, because all the HMMs are trained with the driving data from professional drivers. The most suitable driving behaviours, however, still depend on the current driving environment.

6 Conclusions

A double-layer HMM is developed for driving intention recognition and behaviour prediction using manoeuvring signals and vehicle state measured by a driving simulator. Each multi-dimensional Gaussian HMM (MGHMM) bank in the lower layer corresponds to short-term driving behaviour in a single working case, and upper-layer multi-dimensional discrete HMMs (MDHMMs) are built for long-term driving intention in a combined working case. With a double-layer HMM and online test data, driving behaviour is recognised using lower-layer MGHMMs, followed by driving intention recognition with the recognition results of the lower layer. The driving behaviour associated with a long or near future is also predicted. Experimental results show that our method has achieved high precision and real-time control. Note that the prediction results in this paper are for driving behaviour. Other algorithms should be combined with the proposed method to predict sensor-level data. Our method should be expanded to other combined working cases to enable ultimately auxiliary driving and active safety with the help of a control system.

References

Beyon, J.Y., 2000. LabVIEW: Programming, Data Acquisition and Analysis (1st Ed.). Prentice Hall PTR, Upper Saddle River, New Jersey, USA.

Cappé, O., Moulines, E., Rydén, T., 2005. Inference in Hidden Markov Models. Springer, USA.

Chen, S.G., Ji, S.Y., Liu, W.S., Song, Z.Y., Pang, L.J., 2009. Recursive implementation of Gaussian pulse shaping based on wavelet analysis. *Acta Phys. Sin.*, **58**(5):3041-3046 (in Chinese).

Ge, M.L., 2006. Study on the Automatic Control of Hill-Start Assist System for AMT System. MS Thesis, Jilin University, Changchun, China (in Chinese).

Guo, K.H., Guan, H., Zong, C.F., 1999. Development and Applications of JUT-ADSL Driving Simulator. Proc. IEEE Int. Vehicle Electronics Conf., p.1-5. [doi:10.1109/IVEC.1999.830603]

Kishimoto, Y., Oguri, K., 2008. A Modeling Method for Predicting Driving Behavior Concerning with Driver's Past Movements. Proc. IEEE Int. Conf. on Vehicular Electronics and Safety, p.132-136. [doi:10.1109/ICVES.2008.4640888]

Kuge, N., Yamamura, T., Shimoyama, O., 2000. A Driver Behavior Recognition Method Based on a Driver Model Framework. SAE Paper, Detroit, USA, No. 2000-01-0349.

Meng, X.N., Lee, K.K., Xu, Y.S., 2006. Human Driving Behavior Recognition Based on Hidden Markov Models. Proc. IEEE Int. Conf. on Robotics and Biomimetics, p.274-279. [doi:10.1109/ROBIO.2006.340166]

Oliver, N., Garg, A., Horvitz, E., 2004. Representations for learning and inferring office activity from multiple sensory channels. *Comput. Vis. Image Understand.*, **96**(2):163-180. [doi:10.1016/j.cviu.2004.02.004]

Pentland, A., Liu, A., 1999. Modeling and prediction of human behavior. *Neur. Comput.*, **11**(1):229-242. [doi:10.1162/089976699300016890]

Rabiner, L.R., 1989. A tutorial on hidden Markov models and selected applications in speech recognition. *Proc. IEEE*, **77**(2):257-286. [doi:10.1109/5.18626]

Raksincharoensak, P., Mizushima, T., Nagai, M., 2008. Direct yaw moment control system based on driver behavior recognition. *Veh. Syst. Dyn.*, **46**(sup1):911-921. [doi:10.1080/00423110802037156]

Takano, W., Matsushita, A., Iwao, K., Nakamura, Y., 2008. Recognition of Human Driving Behaviors Based on Stochastic Symbolization of Time Series Signal. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, p.167-172. [doi:10.1109/IROS.2008.4650671]

Wang, W.Z., 2000. t test—the superlative test to discard abnormal values with σ unknown. *J. Sichuan Univ. Sci. Technol.*, **19**(3):84-86 (in Chinese).

Xi, Z., Levinson, D., 2006. Modeling intersection driving behaviors: a hidden Markov model approach (I). *J. Transp. Res. Board*, p.16-23.