Target Lane Changing Prediction Method for ACC System

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ABSTRACT: To improve the safety of adaptive cruise control system (ACC), experiment platform was built up. We obtained the movement state data of the host vehicle and vehicle ahead. Based on the distance between them, the lateral and longitudinal velocity, using Hidden Markov theory, we set up lane change intention prediction model of the vehicle ahead, which tested by the measured data. The results show that the prediction accuracy of the straight line section is 97% and in the curve section is 96%.

INTRODUCTION

Adaptive cruise control system makes the driving people control the vehicle in an emergency situation more convenient and safe, also plays a major role in the development of traditional vehicle to the unmanned vehicle. Because the difference of driver's quality and driving safety consciousness is big, in practical traffic flow, some other vehicles often appear in front of the vehicle suddenly or forcibly squeezed into the vehicle’s lane. In this case, the ACC system equipped on the vehicles will switch tracking target frequently, which resulted in constantly anxious acceleration, deceleration behavior and bad impaction on driving safety and comfort. Therefore, if we can predict the motion state of the front vehicle, the ACC system can deal with the situation advance to keep the safety distance and improve the safety of the vehicle.

At home and abroad there is a lot of research on lane changing intention prediction, the representative of which are: Jang Y M et al. (2014) characterized drivers' pupil size and recognize the lane keeping and lane changing behavior by the method of the support vector machine. M Fitch et al. (2009) divided the look at area into 8 categories, proposed method that the 3.0s is the time window for lane change intention detection; Zheng (2013) obtained lane change intention prediction method of car using fuzzy reasoning theory; Hou (2014) established lane changing intention recognition model, focusing on comparing the different parameters effect; Yuan et al. (2013) using the eye tracker to capture eye movement data in the driving process; Peng et al. (2013) combined with visual feature and vehicle motion state parameters; Li et al. (2013) used extended Kalman filtering method for the vehicle lane change intent recognition.

In summary, the present research is mainly concentrated on own vehicle, not been carried out on the other vehicle lane changing behavior recognition and prediction. Chinese drivers' driving habits are not standard, which brings great challenges to the existing ACC system work algorithm. To this end, the author will use Hidden Markov
MODEL BUILDING

1 Hidden Markov theory  The Hidden Markov model is the development and extension of the Markov model. It is a probability model for the parametric representation to describe the statistical properties of the stochastic process, and also it is a double stochastic process. It is consisted of the Markov chain and random process, as shown in figure 1.

![Figure 1. Composition of Hidden Markov model.](image)

Hidden Markov model is defined as follow (He, 2011):

1) $X$ represents a set of state sets,  $X = \{X_1, X_2, \ldots, X_N\}$, $N$ represents the number of states,  $q_t$ represents the state of the $t$ moment.

2) $O$ represents a set of observable sequences,  $O = \{O_1, O_2, \ldots, O_M\}$, among them,  $M$ is the number of different observed values from each state.

3) Status transition-probability matrix $A = \{a_{ij}\}$, where $a_{ij} = P\{q_{t+1} = S_j | q_t = S_i\}, 1 \leq i, j \leq N$

4) State $j$ observation probability matrix $B = \{b_j(k)\}$, The state $j$ outputs the probability of the corresponding observation value, which $b_j(k) = P\{O_t = V_{k} | q_t = S_j\}, 1 \leq j \leq N, 1 \leq k \leq M$.

5) Initial state distribution $\pi = \{\pi_i\}, \pi_i = P\{q_1 = S_i\}, 1 \leq i \leq N$.

Therefore, the Hidden Markov model can be expressed as a 5-tuple: $\lambda = (X, O, A, B, \pi)$.

Referring to the Hidden Markov model, the front vehicle lane changing motion state is introduced, as follows:

1) $X = \{X_1, X_2, X_3\}$, among them,  $X_1$ represents that the lane is maintained;  $X_2$ represents the change to the left lane;  $X_3$ to the right.

2) $O = \{O_1, O_2, \ldots, O_m, O_n\}$, among them,  $O_i = f(d, V_x, V_y)$;  $d$ represents the lateral distance between the vehicle and the lane in front of the vehicle, cm;  $V_x$ represents the lateral velocity of front vehicle, km/h;  $V_y$ represents the longitudinal velocity of vehicle ahead, km/h.

3) Transition-probability matrix of the front vehicle movement: $A = (a_{ij})_{3 \times 3}$,  $a_{ij}$ represents the probability of the moving state transition of the ahead vehicle.

4) $B = (b_j)_{3 \times n}, b_j$ represents the probability of the observing state $O$ of the ahead vehicle under the condition $X$.

5) $\pi$ represents an initial state distribution.

2 Straight line segment prediction model  Assume that the own vehicle $F$ and the
front vehicle H are running in straight line segment (Figure 2). The own vehicle F drives in the Lane 1, and the front vehicle H in the lane 2. Lane width is recorded as W, the distances between the car and the left and right lanes are \( d_L \) and \( d_R \) is the distance between H and the front vehicle R, lateral distance and angle respectively are \( r \), \( D \) and \( \alpha \). And the distance between the front vehicle H and the left lane is \( d \). The front vehicle’s lateral and longitudinal speed are \( V_x \) and \( V_y \).

In the above mentioned parameters, the parameters who can directly indicate the lane changing intention of the front vehicle H are \( d \), \( V_x \), \( V_y \), and among them, the characterization of \( D \) is the most obvious.

![Figure 2. The relationship in linear section.](image1)

![Figure 3. Relationship in curve.](image2)

In terms of the vehicle-road parameters cooperative interaction mechanism, the parameters \( d \) will change according to a certain rule in the lane changing process, and this change process directly reflects the lane changing intention of the vehicle H. After the beginning of changing lane, the lateral speed of the front vehicle H will present certain characteristics, and this characteristic is different from the lateral speed caused by vehicle’s body sway in normal course of driving. In addition, the parameter \( V_y \) will also increase or decrease. Based on the above analysis, \( d \), \( V_x \), and \( V_y \) are used as the characterization parameters in the prediction model of straight line segment, which can be used to predict lane change intention of H.

3 Curve link prediction model

Compared to the straight line section, because of the influence of the road curvature, the parameter \( D \) in the curve section cannot be directly obtained. Therefore, in order to get the parameter \( D \) and establish the curve section prediction model we first need to measure the curvature of the intermediate parameters. We use the following methods to measure the road curvature in the course of vehicle (Zhan, 2014):

\[
C = \frac{\omega}{v} = \frac{1}{R}
\]

Where: \( C \) is for road curvature, 1/m; \( V \) is for vehicle circumference motion speed, \( v = R \times \beta / t \), unit of \( \beta \) is rad, \( \beta \) is the central angle for vehicles corresponding to the arc length in t time. The unit of t is s, and the unit of \( v \) is m/s; \( \omega \) is the yaw velocity measured by the vehicle gyroscope, rad/s; \( R \) is the curvature radius of the
In the prediction model of the curve section, the $d$, $V_x$ and $V_y$ are used to predict the lane changing intention of the front vehicle $H$.

4 Parameter acquisition The actual road test, we select the common vehicles as the test instruments, which integrate the installation of vehicle radar sensor, lane detection sensors, on-board gyroscope and vehicle controller area network and can bus data acquisition equipment and so on.

5 State parameter filter In figure 2 and figure 3, the driving speed of the vehicle $F$ comes from the vehicle CAN bus, the speed of the front vehicle $H$ can be calculated by the vehicle $F$’s speed and the radar measurement of the two vehicles relative velocity superposition calculation (Wang, 2012). On the basis of this, the vector decomposition principle is used to get the velocity component $V_x$ and $V_y$ of the front vehicle $H$. During the experiment, the outputted raw data measured by the sensors exist certain noise, in order to ensure the effectiveness and accuracy of the Hidden Markov prediction model, before training, the model need to filter the raw measurement data to reduce the noise data and improve the internal data potential connection characteristics. The filtering effect of Kalman filter is shown in Figure 4 and figure 5.

THE TRAINING AND TESTING OF THE MODEL

1 The model training and optimal time window selection The data of some lane keeping and lane changing are selected from the front vehicle motion state data obtained from the actual road driving test. Among them, 648 groups of the data are used for model training, and 216 groups for the model validity test. In the training process, the 1.0s time window is continuously identified, and the time interval of each data movement is set to 0.1s. The training samples have already been set tag attributes. Therefore, through training the different motion state of the front vehicle $H$, Hidden Markov model will analysis continually to determine the potential relationship
between the internal characteristics of the data and the property tag. The data training process is shown in figure 6.

![Figure 6. Moving time window.](image)

After the model training, the validity of the model is tested by the measured data. Among them, the result of the model is the probability that the output of the model is inclined to some state. If the probability value is close to 1, it indicates that when in the next time window the probability of the vehicle in the corresponding state is higher. For a complete lane changing behavior, 1.0s is used as the prediction time window length, and the model prediction results are shown in table 1.

**Table 1. Model predictions.**

<table>
<thead>
<tr>
<th>Forecast probability</th>
<th>L_\text{K}</th>
<th>L_\text{CL}</th>
<th>L_\text{CR}</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.86</td>
<td>0.53</td>
<td>0.14</td>
</tr>
<tr>
<td>Forecast result</td>
<td>L_\text{K}</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In Table 1, L_\text{K} indicates the lane keeping; C_\text{L} indicates the left lane changing; L_\text{CR} indicates the right lane changing. From table 1, we can see that in the corresponding time period, in the next time the window, the front vehicle in the lane keeping state maintains a probability of 0.86, much higher than the left and right lane changing probability. As a result, the predicted result for the model outputs is lane keeping.

In addition to predicting accuracy, the real-time ability is also an important factor to predict the actual application value of the model. (Lv et al., 2010). Therefore, by analyzing and comprising forecasting effect in different length time windows, it can effectively meet the requirements of accuracy and real-time performance of prediction for ACC and other systems.

Because there are great differences in the method of identifying the position between the straight line and the curve section, the 2 sections are separated in the model training and testing process. In the interval of 0.5 ~ 5.0s, using 0.5s as the interval, the validity of the model was tested under different time window length, and the results are shown in table 2.

**Table 2. The prediction accuracy of different time windows.**

<table>
<thead>
<tr>
<th>Time window (s)</th>
<th>0.5</th>
<th>1.0</th>
<th>1.5</th>
<th>2.0</th>
<th>2.5</th>
<th>3.0</th>
<th>3.5</th>
<th>4.0</th>
<th>4.5</th>
<th>5.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast accuracy (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Straight line segment</td>
<td>70</td>
<td>73</td>
<td>77</td>
<td>84</td>
<td>88</td>
<td>90</td>
<td>95</td>
<td>96</td>
<td>97</td>
<td>95</td>
</tr>
<tr>
<td>Curve section</td>
<td>50</td>
<td>65</td>
<td>73</td>
<td>87</td>
<td>91</td>
<td>94</td>
<td>96</td>
<td>95</td>
<td>95</td>
<td>94</td>
</tr>
</tbody>
</table>
From the table 2, we can see, the prediction accuracy of straight line and curve line shows a trend of increase. When the time window reaches 3.0s, the prediction accuracy of straight line and curve line are more than 90%. With the time window increase continually, the prediction accuracy will continue to increase, when reaching a certain peak, the prediction accuracy of the 2 lines will be in a certain degree of decline. For straight line segments, when the time window length is 4.5s, the prediction accuracy reaches the maximum value of 97%. For the curve line, when the time window length is 3.5s, the prediction accuracy reaches the maximum value of 96%.

2 Forecast effect In order to further study the prediction performance of the model, we get the optimal time window length value from Table 2. For straight line, the time window length is 4.5s. Time starting from 4.5s before the start point, 0.1s as the unit, the time window going from the left to right, we obtained the model predicted lane changing time of the vehicle H, the results shown in figure 7.

![Figure 7. Prediction effect of the model in straight sections.](image1)

From Figure 7, we can see that, 4.5s before the starting point, the Hidden Markov model started to predict the front vehicle’s lane change intention. From the point of the lane changing beginning, after the 1.2s, the model can predict the correct behavior. In the curve line, the time window length is 3.5s, and the same processing method is adapted to the curve line section. The prediction effect of the model is shown in Figure 8.

![Figure 8. Prediction effect of model in curve sections.](image2)
In Figure 8, Compared to the straight section of the 1.2s, the curve of the forecast time is only 1.0s. Analyzing the reasons, in straight sections the running speed of the vehicles usually is higher than in the curve sections. And in the same time window the data the straight sections contained is less than the curve sections. Thus, the prediction time is longer than the curve sections.

CONCLUSIONS

1) For the straight line and the curve section, with the increase of time window, the accuracy rate of the prediction model presents an upward trend. In line section when the time window length is 4.5s, the accuracy rate of the prediction reached the maximum value of 97%. In the curve section, when the time window length is 3.5s, the accuracy rate of the prediction reached the maximum value of 96%.

2) Compared to the straight line section, the predicted optimal time window in the curve section is shorter.

3) On the straight road, 1.2s after the front vehicle began to change lane, the prediction model can accurately predict the behavior, and the time value is 1.0s in the curve section.

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REFERENCES


