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Recognition and Analysis on Overtaking Behavior

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Abstract: This study has a research of HMM and recognizes current driving intention, Moreover, using time to judge whether the behavior is overtaking behavior or not. Next, MSS was used to judge whether the overtaking conditions met or not. In addition, if they do not meet there will be a warning for driver. Use Gauss density functions to improve P-2D-HMM and discriminate driving intention, then identify the overtaking behavior. Based on vehicle kinematics theory, judge whether the overtaking behavior is normal by SMM. Warn the drivers whose overtaking behavior is abnormal to expect to reduce the traffic accident caused by overtaking. The result of experiment confirms that the model can accurately recognize overtaking behavior and the abnormal overtaking can be effective identified.

Keywords: Gauss density function, overtaking, P-2D-HMM, SMM

INTRODUCTION

How to effectively improve vehicle active safety performance in intelligent vehicle research and development process is an important part researchers concerned. The real-time driver reaction behavior data, gathered by Electronic Auxiliary Driving System, are used to assist drivers in operating vehicles. That is, in essence, driving behavior research. Overtaking behavior is the most frequent in the series driving behavior. It can be considered as speed-changing and lane-changing. The number of traffic accidents caused by lane-changing is approximately 4~10% of the total traffic accidents (Li-sheng *et al*., 2009) and on highway is 20%, bringing huge economic loss to society. At present, overtaking research at home and abroad is mainly about studying lane-changing process from different aspects and overtaking intention models are mainly based on Fuzzy Reasoning Model, Hidden Markov Model and Artificial Neural Network Model and related improved models and so on. These models propelled the research of overtaking research, but there are still some drawbacks when these models described the real process. For example, they merely identify a single lane-changing behavior, but in the real overtaking environment, overtaking behavior is a series of driving behavior rather than a single one. Li-sheng *et al*. (2009) study the safety lane change model of vehicle assistant driving on highway. Wang *et al*. (2005a, b) study the inference of driver's intentions based on fuzzy reasoning. Zhang (2004) have a research of the modeling and applications of hidden markov models. Wang *et al*. (2010) analyse the minimum safety distance of lane changing based on virtual reality. Hsiao (2008) study the time-varying system identify-ication via maximum a posteriori estimation and it s application to driver steering models. Berndt *et al*. (2008) have a research of the continuous driver intention recognition with hidden markov models. Yoshifumi and Koji (2008) study the modeling method for predicting driving behavior concerning with driver's past movements. Tian and Chaoyin (2007) analyse the rand course analyses and apply. Sun and Wang (2001) study the fuzzy discernment of the driving environment and the driving intention in amt.

Based on the analysis of previous research results, this study improved Pseudo 2-D Hidden Markov Model (P 2D HMM), using Gaussian distribution, one characteristic of which is continuity that can describe continuity of driving. We called the improved model C-P2D-HMM, which can discriminate the intention of speed-changing and lane-changing. Then identify overtaking behavior using overtaking time.
The advantage of this model is:

- The Gaussian distribution can better describe vehicle space-time continuity
- The Markov chain in treatment of non-stationary random sequence has distinct advantage
- This model is 2-dimension, which improves the real degree of reality description to a certain extent

After that, judge the overtaking behavior is normal or not by using the Vehicle Dynamic Principle. For abnormal overtaking behavior, the system will warn

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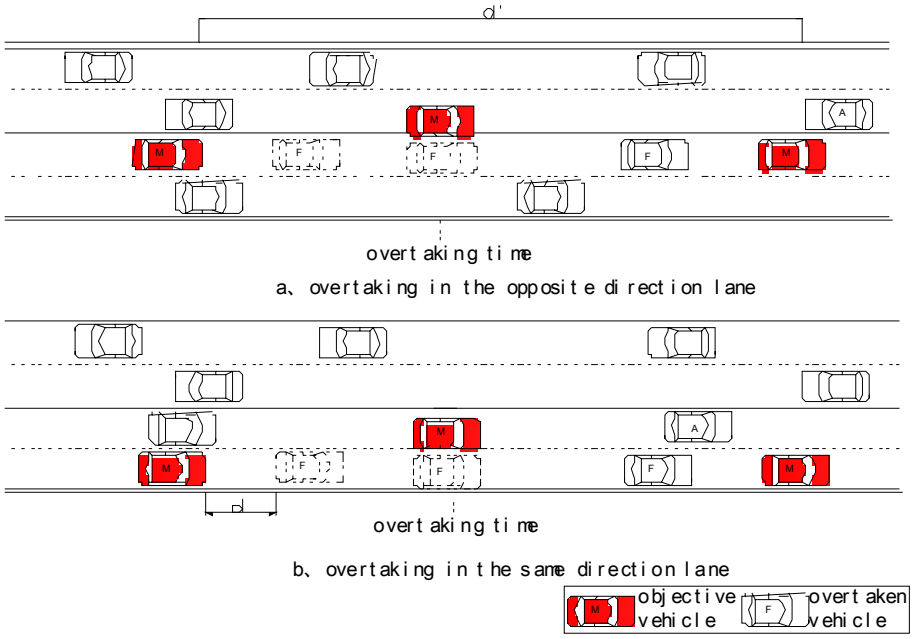

Fig. 1: Overtaking condition schemes

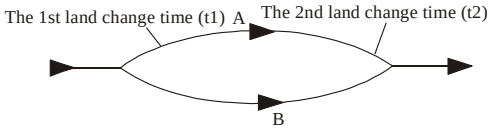

Fig. 2: Overtaking trajectory scheme

driver. In which way the number of traffic accidents maybe decline.

OVERTAKING BEHAVIOR IDENTIFICATION

Overtaking condition: The condition of driving directly affects driver's driving behavior. For the overtaking behavior, this study will divide overtaking condition into two parts, overtaking in the opposite direction lane and in the same direction lane. The former is using reverse fast lane overtake vehicle F, which usually occurs in the urban road without intervening belt; the later is using coincidental lane overtake vehicle F from left lane, as shown in Fig. 1. Although overtaking from right is illegal (Fig. 2), there are still some drivers holding fluky psychology. These behaviors bring traffic safety huge hidden trouble.

Driving intention recognition mode l: Overtaking intention is not visible, so the vehicle driving process is usually used to describe it. Driving process has the space-time continuum and is a series of complex activities results. In order to facilitate this process, overtaking behavior is regarded as drivers finishing two times lane-changing and speed-changing in a certain time Δt. This needs to jump out the limits of one dimension and using two dimension models instead of one dimension is more reasonable.

P2D-HMM, based on HMM, is an incomplete statistics model (Zhang, 2004). It is applicable to dynamic modeling and widely used in domains of face recognition and character recognition. Its double stochastic process comprises an invisible finite state 2D markov chain and a random process. The former can be used to describe the transfer of overtaking intention and the later can be used to describe the relationship between overtaking intention and overtaking behavior, which can use observation probability to describe. The C-P2D-HMM is based on P2D-HMM, so the model also has these characters. Through the transition probability of overtaking intention the later driving intention can be forecasted.

Related parameters of P2D-HMM: $\Gamma = (\Pi, A, B, S, V)$ can be used to describe P2D-HMM. $\Pi = \{P_q\}$ is the initial probability distribution and $P_q = P(X_{1,1} = q)$.
$A = \{P_{q|r}, P_{q|t}, P_{q|r,s,t}\}$ is the transition probability distribution. $P_{q|r}$ is the first column of the transition probability distribution, $P_{q|r} = P(X_{m,1} = q|X_{m-1,1} = r)$; $P_{q|t}$ is the first line of transition probability distribution, $P_{q|t} = P(X_{1,n} = q|X_{1,n-1} = t)$; and $P_{q|r,s,t}$ is the others of the transition probability distribution:

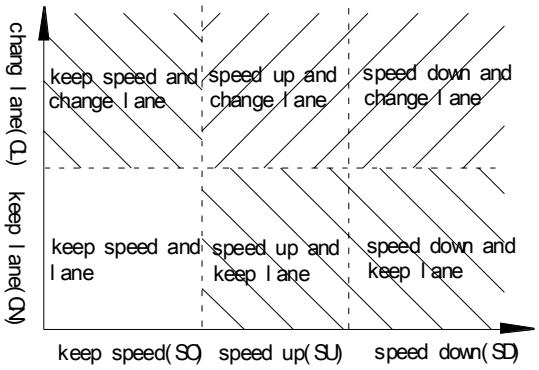

Fig. 3: 2 dimensions of the model

$$P_{q|r,s,t} = P(X_{m,n} = q \left| \begin{array}{l} X_{m-1,n-1} = s \\ X_{m,n-1} = t \\ X_{m-1,n} = r \end{array} \right.)$$

$B = \{P_q(\varsigma_i)\}$ is the observed characteristics probability distribution:

$$P_q(\varsigma_i) = P(Y_{m,n} = \varsigma_i | X_{m,n} = q)$$

$S = \{q, r, ..., w, y, z\}$ is the limited space set.
$V = \{\varsigma_i\}$is the discrete set of observed characteristics.
In addition, $X = X^{M,N}_{1,1} = \{X_{m,n}: (m, n) \epsilon L\}$ is $M \times N$ dimensional state matrix; and $Y = Y^{M,N}_{1,1} = \{Y_{m,n}: (m, n) \epsilon L\}$ is $M \times N$ dimensional observed characteristics matrix.

Driving intention identify model based on C-P2D-HMM: Overtaking behavior can be regarded as the combination of speed changing and lane changing and the model's 2 dimensions can be determined which is based on the two intentions. Then based on the model, the speed changing and lane changing can be identified, just as Fig. 3 shows. Keeping speed and changing lane, speed up and keeping lane and speed down and keeping lane can be regarded as 1-dimensional observation sequence changing, but the other two situations, speed up and changing lane and speed down and changing lane, need the 2-dimensional observation sequence changing at the same time, which the P2D-HMM can meet the requirements.

And the driving is continuous time behavior, but the observed characteristics probability distribution B in P2D-HMM is discrete distribution. If using the model to directly identify driving intention, there are must be some errors in the results. So the P2D-HMM should be improved. Gaussian mixture probability density is used to describe the continuous observation sequence. Its observation vector sequence is $O = \{O_1, O_2, ..., O_K\}$.
$\Gamma = (\Pi, A, C, \mu, U)$ can be used to describeC-P2D-HMM.
$\Pi = \{P_q\}$ is the initial probability distribution of driving intention and $P_q = P(X_{1,1} = q)$.

$A = \{P_{q|r}, P_{q|t}, P_{q|r,s,t}\}$ is the transition probability distribution of lane and speed. $P_{q|r}$ is the transition probability distribution of keeping speed, $P_{q|r} = P(X_{m,1} = q|X_{m-1,1} = r)$; $P_{q|t}$ is t transition probability distribution of keeping lane, $P_{q|t} = P(X_{1,n} = q|X_{1,n-1} = t)$; and $P_{q|r,s,t}$ is the others of the transition probability distribution:

$$P_{q|r,s,t} = P(X_{m,n} = q \left| \begin{array}{l} X_{m-1,n-1} = s \\ X_{m,n-1} = t \\ X_{m-1,n} = r \end{array} \right.)$$

$$C = \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1k} \\ C_{21} & C_{22} & \cdots & C_{2k} \\ & \cdots & & \\ C_{j1} & C_{j2} & \cdots & C_{jk} \end{bmatrix}$$ is the mixture weights of Gaussian density and $\sum_{k=1} c_{jk} = 1, c_{jk} \geq 0$.

$$\mu = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1k} \\ \mu_{21} & \mu_{22} & \cdots & \mu_{2k} \\ & \cdots & & \\ \mu_{j1} & \mu_{j2} & \cdots & \mu_{jk} \end{bmatrix}$$ is the mean vector of Gaussian density.
U is Covariance matrix.
Then driving intentions observation sequence V probability density function forms is:

$$b_j(V) = \sum_{k=1} c_{jk} b_{jk}(V)$$
$$= \sum_{k=1} c_{jk} \cdot \frac{1}{\sqrt{2\pi U_{jk}}} \cdot \exp[-\frac{1}{2U_{jk}}(O - \mu_{jk})^T (O - \mu_{jk})]$$

Same with HMM, modeling C-P2D-HMM need to solve learning problems of model, which is to get the related parameters of the model. Then decode the model to work out the optimal sequence of hidden states.

This study optimized Γ and hidden states by cross validation between parameters and model. That is initial parameters Γ_0 is given at first to make sure the most possible states of meeting the parameters group, then parameter Γ is estimated again in the current condition and based on which the model state is revalued. Circulate until conditions of convergence are met. Last calculate Γ to get max $P(V|\Gamma)$ under the input sequence of drivers' operations and random initial parameter Γ_0. This study used 2D Viterbi algorithm to get the optimal state chain.

Overtaking recognition and abnormal overtaking: Recognize driving intention is to help driver operate vehicles better. The drive can be warned if the next identified driving behavior which is abnormal, even using

the computer to control the vehicle not to execute the wrong operation. Three logical stages are usually considered when driver is in overtaking process:

- Whether there is overtaking demand or not
- Whether overtaking condition is mature or not
- Whether overtaking must be taken

Abnormal overtaking is that in the overtaking process the drivers overtake when the condition is not mature because of the divers' psychological factors, driving environment factors and so on. But illegal overtaking doesn't belong to abnormal overtaking behavior. It takes huge negative effects to road traffic safety. Abnormal overtaking may caused scraping among vehicles even collision and death, which directly affects transportation capacity. According to Minimum Safety Space (MSS), whether the overtaking is normal or not is judged. The MSS between object vehicle M and vehicle A and the MSS between object vehicle M and vehicle F is respectively got by using motion characteristics in overtaking process, just like Fig. 1 show (Wang *et al*., 2010):

$$MSS(A,M) = \max\{\int_0^t\int_0^\lambda [a_M(\tau) - a_A(\tau)]d\tau d\lambda + [v_M(0) - v_A(0)t, 0\} \quad (1)$$

$$MSS(F,M) = \max\{\int_0^t\int_0^\lambda [a_M(\tau) - a_F(\tau)]d\tau d\lambda + [v_M(0) - v_F(0)t, 0\} \quad (2)$$

When the two conditions are not met, the overtaking condition is not considered maturity and the overtaking is abnormal.

MODEL CONFIRMATION

Figure 4 is the framework of driving intention recognition that is based on C-P2D-HMM. In the known sample data, select the first 5/6 data as the training sample of C-P2D-HMM SXCY and the others as confirmation sample.

If it contains the lane changing intention in one driving intention, the time t_1 is recorded and the rest can be done in the same manner $t_2 \ldots\ldots t_n$. An overtaking behavior is considered if t_n-$t_{n-1} \in \Delta t$. And the range of Δt depends on the lane width, object vehicle speed and overtaken vehicle speed.

Classification training: If overtaking is in the opposite direction lane, the input data should consider the space between object vehicle M and vehicle A, the relative velocity between object vehicle M and vehicle A and lateral acceleration of M, but because of limiting of sample data, the model with this condition will not be trained.

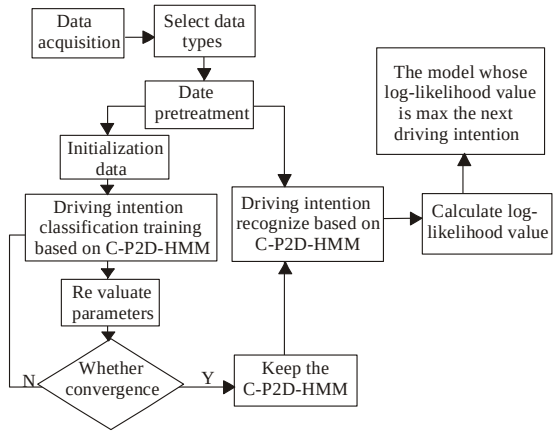

Fig. 4: The framework of driving intention recognition that is based on C-P2D-HMM

The sample dada type belonged to overtaking in the same direction lane. This study used the space between two vehicles, speed and steering wheel angle three kind data to get the needing dada. The horizontal speed curve and horizontal acceleration curve could be got by speed curve and steering wheel angle curve. So the space between two vehicles, the objective vehicle speed and the horizontal acceleration were as input data to train and get the driving intention recognize model based on C-P2D-HMM, namely C-P2D-HMM SUCL, C-P2D-HMM SUCN, C-P2D-HMM SOCL, C-P2D-HMM SOCN, C-P2D-HMM SDCL and C-P2D-HMM SDCN. Then revaluate the parameters of these models, test whether it is convergence. If yes, the model could be kept as the driving intention recognize model based on C-P2D-HMM.

Then use the kept models to respectively recognize the driving intention and use log-likelihood to estimate the likelihood level of C-P2D-HMM. When iterative result difference value is less than 10, the model likelihood level is considered well. All of the sample data were input in the models respectively and used log-likelihood to estimate every model. Which model the kind data belonged to, the current driving intention could be identified? That solved the estimate problem, which model is the most possible model under the observation sequence. Table 1 is a set of driving intention log-likelihood value.

While the sample data was input in the model, the recognized results we got were shown in the Table 1. It showed that only one model's likelihood is largest with a

Table 1: Log-likelihood value of driving intention based on C-P2D-HMM

	SUCL	SUCN	SOCL	SOCN	SDCL	SDCN
Keep speed and change lane	-105.9903	-124.6652	-63.5930	-112.0324	-133.7730	-145.2383
Keep speed and not change lane	-117.3658	-112.9266	-101.3275	-79.0491	-121.4217	-125.5391
Speed up and change lane	-51.3510	-87.2997	-114.4401	-107.2800	-114.3396	-153.9162
Speed up and not change lane	-78.2587	-59.8041	-137.9436	-115.2738	-105.3587	-118.4191
Speed down and change lane	-103.3685	-114.2206	-109.8376	-132.8834	-81.3349	-109.8201
Speed down and not change lane	-111.3984	-102.7286	-142.3079	-128.7239	-115.3019	-73.7315

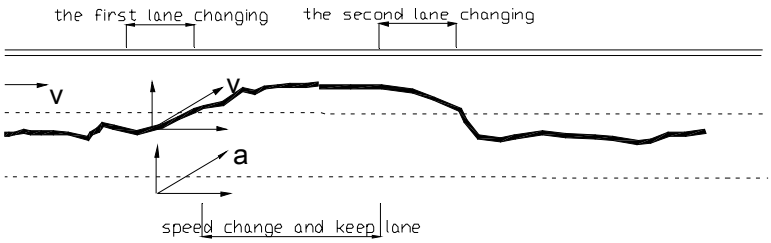

Fig. 5: The vehicle trajectory

set of sample data was input in the model. Speed up and lane changing as example shown in Table 1, the homologous data was input in C-P2D-HMM SUCL, then the log-likelihood was -51.3510. Compared with other models log-likelihood value, it was the max likelihood output. So it was ideal classification.

Based on the above result, the driving intention of next time can be preliminary predicted. While 5s is as the time interval to divide the sample and the data in the 5s respectively input to the model, 6 probability value will get in which the max value is the corresponding driving intention. The model SUCL as an example, in a certain time interval, the probability values got from the model respective are 0.7413, 0.0438, 0.1674, 0.0137, 0.0143 and 0.0195, which means that the next possible operation is speed up and lane change. All of the sample data were input the model and the accuracy was about 93.15% which meant the next driving intention could be accurately identified. While 3s is as the time interval to divide the sample and the data in the 3s respectively input to the model, the accuracy was 95.44%. With the decrease of the time interval, calculation of the model increased but the accuracy improved.

Besides considering forecast precision, the model also needs to consider how earlier before the behavior operate, namely the prediction ability in advance of the model.

Predict time in advance = the moment of the actual behavior happening-the moment of predict driving intention happening.

It is found that the more Gaussian mixture number is, the shorter recognizing time needs. When the number is 4, the time is 3.7s and the number is 8, the time is 1.4s.

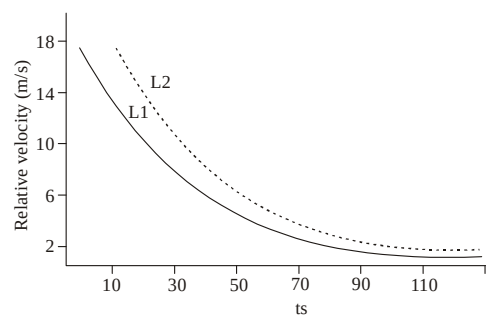

Fig. 6: The critical curve of Δt

Overtaking recognize analysis: Recognize overtaking behavior after predicting the next moment driving intention. As shown in the Fig. 5, if the time difference of adjacent two times lane-changing is in the scope of Δt, the overtaking is complete. Δt is determined by the cumulative sum of 3 respective needing times, which are belong to the first speed-changing and lane-changing, the second speed-changing and lane-changing and speed-changing and keep-lane. The width of lane in our country is usually from 3 to 3.5 m, here is 3.2 m. When the horizontal speed of object vehicle is 0.64 m/s, the needing time of the first speed-changing and lane-changing and the second speed-changing and lane-changing is at most 10s. The needing time of speed-changing and keep-lane is determined by relative velocity between overtaken vehicle and object vehicle and the relationship of whom is showed in the Fig. 6. The curve L1 is critical curve of speed-changing and keep-lane and the curve L2 is critical curve of Δt. Two times speed-changing and lane-changing happen in the scope of Δt, an overtaking behavior is

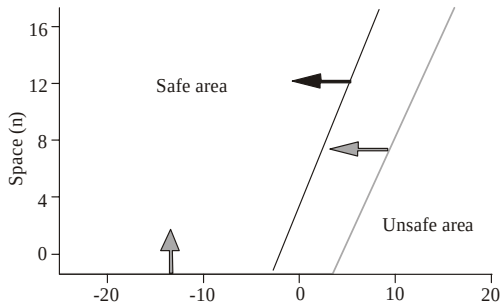

Fig. 7: The safety space between vehicle M and F when it is speed-up and lanechanging

considered to complete. While the time is not in the scope, the behavior is considered a single speed-changing and lane-changing.

According to the related data of vehicle and driving environment at overtaking beginning moment (that is the moment of the first speed-changing and lane-changing), the overtaking behavior can be normal or not, then there will be warnings for driver if it is abnormal. Figure 7 showed the safety space between vehicle M and F when it is speed-up and lane-changing, which got by analyzing the model MSS. The black curve showed the approximation curve of SMM when $V_A > V_F$ and the red curve was the approximation curve of SMM when $V_A > V_F$. The overtaking conditions were met in the safe area, so the drivers could overtake according to their psychological characteristics. And the overtaking conditions were not met in the unsafe area, overtaking at the situation is abnormal and the drivers should be alert.

CONCLUSION

This study carried on preliminary exploratory research of HMM and based on which using Gaussian density function improved P-2D-HMM to recognize current driving intention, then using time Δt to judge whether the behavior is overtaking behavior or not. Next, MSS was used to judge whether the overtaking conditions met or not and if they do not meet there will be a warning for driver. The result of experiment confirms that the model can accurately recognize overtaking behavior and the abnormal overtaking can be effective identified.

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