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Prediction of Un-safety Driving Status in Automotive Vehicle Based on Hidden Markov

***Abstract**. Based on Hidden Markov Model, a new prediction method on driving status is advanced. In which, the velocity of following car, the velocity difference and distance headway is input as observation variables, the driving status is output as hidden variable. First the probability of observation status needed is calculated by forward algorithm, then the probability of observation status and driving status appeared together is calculated, at last, the prediction value of driving status could be got by conditional probability. The warning character of the prediction method could be evaluated not only by the accuracy but also by a new index ⊿ATp, which could show the degree of warning time at p probability. The results of simulation show that the method is right, which is in agreement with the result of eye movement checking method named PERCLOS, and it could complete the prediction: when P%= 30%, ⊿ATp = 2min7 sec, when P%= 40%, ⊿ATp = 1min51 sec; when; when P%= 50%, ⊿ATp = 56 sec, when P%= 60%, ⊿ATp = 34 sec.*

***Streszczenie.** Bazując na ukrytym modelu Markova przedstawiono nową metodę przewidywania status pojazdu. Jako obserwowalne zmiany podaje się szybkość pojazdu z tyłu, odległość a jako zmienne ukryte status pojazdu. (**Przewidywanie niebezpiecznej sytuacji pojazdu samochodowego bazujące na ukrytym modelu Markova**)*

Keywords: traffic engineering; driving status; HMM; prediction; probability.
Słowa kluczowe: inżynieria ruchu, pradopodobieństwo, przewidywanie.

Introduction

With the rapid development of economic and the fast increase of vehicle number every year, "Driver" is no longer a professional; the person who obtained a driver's license can be widely known as "driver". The rapid growth of drivers have led to the disparity of driving level is further. At the same time the traffic information may be more and more complex which can be obtained. So the driving status is more and more unstable in the driving process. The driver is a regulator and controller in human-vehicle-road transport system, his or her status is important for traffic safety. The accident occurred on the road with people-related accounted for 31% of the total [1]. Therefore, the real-time monitoring of driving status is an important research of active safety defense capability in intelligent transportation security. At present, there are EEG, ECG, PERCLOS, eye movement check, face recognition, steering wheel movements monitoring, lane departure monitoring, etc. for monitoring driver status [2]. Methods based on EEG and ECG are better accuracy, but they are incursive which would affect the drivers normal driving psychology. The accuracy of eye movement check, face recognition, steering wheel movement monitoring and lane departure is low. PERCLOS is a commonly used method, but it has certain requirements on the statistical time. The velocity of following car, the velocity difference and distance headway is input as observation variables, the driving status is output as hidden variable, a new prediction method on driving status is advanced, based on Hidden Markov Model. A new index ' ΔAT_P ' is established to evaluate how long the method could predict. The results of simulation show that the method is right, which is in agreement with the result of eye movement checking method named PERCLOS and it could complete the prediction.

Driving Status Analysis

The changing of driving status, distinguished into normal driving status and abnormal driving status, is usually caused by drivers fatigue or stress. Normal driving status is that the drivers are sober, focused and agile, make the right judgments on the surrounding environment and the emergency situation, and can make quick and accurate response to deal with emergency or accidents etc. When the driver is spirited and conscious, the possibility of accidents is very little. Abnormal driving status is that the drivers, whose mind is drowsy, vision is loss, the situation is distraction and unresponsive and stiff, and misjudgment rate is high, can easily lead to accidents [3].

Currently, the research on driving status mainly contains alcoholism, fatigue, physiological and psychological changes while the driver is nervous, and monitoring technologies for these status changes [4]. Related outcomes have been achieved at home and abroad include that: alcohol monitoring, a method that the alcohol content can be detected by alcohol detection sensor. If it is too high, driver can not start his car; EEG monitoring, using the average power of spectral density in different frequency bands at different brain wave status to identify. This method is in high accuracy and the real time is good. But the signals acquisition need to contact which will affect the normal driving, and brain waves change very different from individual and environment that is difficult to give a unified quantitative standards; ECG monitoring, using the ECG time-frequency domain index to identify, whose effect is good, but the measurement is under harsh conditions; PERCLOS monitoring, using eyes closed extent accounted for more than 80% of the time, the percentage of a certain particular time to identify; Pupil monitoring , using pupil diameter under different conditions to identify, belongs to a non-contact monitoring. There are also the head displacement monitoring, steering wheel movement monitoring ,lane departure monitoring and so on, but the error rate of these methods is high[5 , 6,7].

Hidden Markov Model (HMM)

Hidden Markov Model (HMM) is an extended Markov model, the basic theory of which was formed in the late 60s and the early 70s of last century, and has been widely applied in speech recognition [8]. Hidden Markov Model describes a double random procession, one of which can not be directly observed and described by status transition probability matrix. Another random process output the observation symbol that can be observed, is defined by the output probability. Model λ can be expressed as a five-group [9]:

Let $\lambda = (S, O, A, B, \pi)$,

In which:

S is the hidden status, and $S=(S_1,S_2,S_3,\Lambda,S_n)$;

O is observed status, and $O=(O_1,O_2,O_3,\Lambda,O_n)$;

A is the status transfer matrix, which have N lines and N ranks.

(1) $$A=\left[a_{ij}\right], a_{ij}=P(q_{t+1}=j|q_t=i) \quad 1\le i,j\le N$$

q_t is the status of random sequence at t, $q_t\in S$;

B is confounded matrix, and $B=\left[b_j(k)\right]$.

$b_j(k)$ is the probability of output O_k in status j, and $b_j(k)=P(O_k|j), 1\le k\le M, 1\le j\le N$.

π is the initial status probability distribution, and $\pi=\{\pi_i\}, \pi_i=P(q_1=i)$ is a certain status probability at the moment 1.

HMM have three main applications [10]: (1) Assessment. According to the known HMM to find the probability of an observation sequence, Forward Algorithm and Backward Algorithm are common used. (2) Decoding. Find the most likely hidden status sequence based on observation sequence, commonly use the Viterbi Algorithm. (3) Study. Based on the observation sequence and the hidden status, a triple HMM (A,B) is formed to make this triple can be best described as a phenomenon we have seen, the Baum-Welch Algorithm is usually used.

Driving Status Prediction Model

Driving status is uncertain and not visible, and can be expressed by the random process of controlled vehicles in some extent. Observed driving status was not correspondence with the vehicle random process, but linked to a group probability distribution. HMM has a strong time-series, and can predict the driving status after a period of time according to driving status transition probability. Using hidden Markov model to predict the driver status, the meaning of the parameters set are as follows:

S is the driving status, and $S=(S_1,S_2)$. S_1 is normal driving status, that is $PERCLOSE80<0.15$; S_2 is abnormal driving status, that is $PERCLOSE80\ge 0.15$.

O is observed status, which is made up by the 3 dimension of $\Delta v, v_f$ and d. They can be obtained at any time, and $O=(O_1,O_2,O_3,\Lambda,O_n)$.

$\Delta v, v_f$ and d need to be normalized at first, and the same status of which should be combined, and the steps were showed in reference[10].

A is the transfer probability of different driving status, and $A=\left[a_{ij}\right]_{2\times 2}$.

B is the observed sequence probability of different driving status, and $B=b_j(k)_{2\times n}$.

π is the initial driving status probability.

The parameters A,B,π need to make the offline training by the Baum-Welch algorithm in reference [11]. The initial value of training set by percentage of sample data statistics.

Therefore, the driver status prediction model can be described as: using the trained HMM model to find the desired observation sequence corresponding to the probability of hidden status $P(q_t=i,O|\lambda), i=1,2$.

Prediction Algorithm

The probability of a certain status at the future time T is the conditional probability shown in formula (2). That is with the observed sequence $O_1,O_t,\cdots O_{\mathrm{T}}$, the probability of driver status is:

(2) $$P(q_1,q_t,\cdots q_{\mathrm{T}}|O_1,O_t,\cdots O_{\mathrm{T}})=\frac{P((O_1,O_t,\cdots O_{\mathrm{T}})\bullet(q_1,q_t,\cdots q_{\mathrm{T}}))}{P(O_1,O_t,\cdots O_{\mathrm{T}})}$$

That means, the driving status at the time T determined by both the probability $P(O_1,O_t,\cdots O_{\mathrm{T}})$ of observed sequence $O_1,O_t,\cdots O_{\mathrm{T}}$ and the probability $P((O_1,O_t,\cdots O_{\mathrm{T}})\bullet(q_1,q_t,\cdots q_{\mathrm{T}}))$ in the driving status $q_1,q_t,\cdots q_{\mathrm{T}}$ while observed $O_1,O_t,\cdots O_{\mathrm{T}}$.

(1)calculate $P(O_1,O_t,\cdots O_{\mathrm{T}})$

Calculating the $P(O_1,O_t,\cdots O_{\mathrm{T}})$ value is the first assessment problem of HMM, and the Forward algorithm is used to solve the problem. The core problem of prediction is to ensure the hidden and output layers observed sequence status of HMM in prediction time. Considering the aim of driver status prediction is to prevent traffic accidents initiatively [12]. So abnormal driving status is the predict object, the status of the time t was decided by the next formula:

(3) $$O_t=O_t(\Delta v<const(\Delta v), and\ \ v<const(v), and\ \ d<const(d))$$

(3)In which $const(\bullet)$ is abnormal driving status threshold, and decides by the sample data.

The observed sequence in the predicted time T is:

(4) $$M_T^z=(O_1(y),\Lambda,O_t(y),\Lambda,O_T(y)) \quad y=1,2,\Lambda,k(k<n); 1\le t\le T; 1\le z\le k^{T/\Delta t}$$

$O_t(y)$ is the observed status y at the time t. $M^z{}_T$ contains $z=k^{T/\Delta t}$ compound modes, and Δt is interval time.

So:

(5) $$P(O_1,O_t,\Lambda,O_T)=\sum_{z=1}^{k^{T/\Delta t}}P^z(O_1,O_t,\Lambda,O_T)=\sum_{z=1}^{k^{T/\Delta t}}P^z(M^z{}_T) \quad z=1,2,\Lambda,k^{T/\Delta t}$$

(6) $$P^z(M_T)=P^z(O_1,O_t,\Lambda,O_T)=\sum_{1}^{2}[\sum_{i=1}^{n}\alpha_{t-1}(j)\alpha_{ij}]b_j(O_t^Z) \quad 1\le t\le T, 1\le j\le n \quad \alpha_1(i)=\pi_i b_i(O_1^z), 1\le i\le n$$

(3)calculate $P((O_1,O_t,\cdots O_{\mathrm{T}})\bullet(q_1,q_t,\cdots q_{\mathrm{T}}))$

The abnormal driving status is also used to as warning object to calculate the common probability of $((O_1,O_t,\cdots O_{\mathrm{T}})\bullet(q_1,q_t,\cdots q_{\mathrm{T}}))$. It is considered that i=1 is as normal driving status in hidden layer of hidden status q, and i=2 is as abnormal driving status in output layer. Then in time T there is:

(7) $$S^x=(q_1(1),\cdots,q_{T-\Delta t}(1),q_T(2))$$

Let T equal to every positive times value $x(1 < x \le T/\Delta t)$ in Δt, to get the driver status sequence $S^x(1 \le x \le T/\Delta t)$ of every predict point in total predict time T. So:

$$\begin{aligned} &P((O_1,O_t,\cdots O_T)\bullet(q_1,q_t,\cdots q_T)) = P^x(S^x,\sum M^z|\lambda) \\ &= P^x(S^x,M^1|\lambda)+P^x(S^x,M^2|\lambda)+\cdots P^x(S^x,M^z|\lambda) \end{aligned} \tag{8}$$

In which,

$$\begin{aligned} &P^x(S^x,M^z|\lambda)=\zeta_{t-1}(j)\alpha_{ij}b_j(O_t^Z)=\begin{cases} j=1 & t\le T-\Delta t \\ j=2 & t=T \end{cases} \\ &\zeta_1(i)=\pi_i b_i(O_1^z), 1\le i\le n \end{aligned} \tag{9}$$

Therefore the every predict point probability of abnormal driving status in predict time T is that:

$$P(q_1,q_t,\cdots q_T|O_1,O_t,\cdots O_T)=\frac{P^x(S^x,M^z|\lambda)}{\sum_{z=1}^{k^{T/\Delta t}} P(M^z{}_T)},(x(1<x\le T/\Delta t),1\le z\le k^{T/\Delta t}) \tag{10}$$

The steps of driving status predict algorithm based on HMM show in figure 1:

Step1: initialization. Set the predict time T, the number of observed sequence status n in Δt, and driving status i=1, 2; Let z=0, x=0;

Step2: get M^z, S^x based on formula(3)and(7);

Step3: let z=z+1;

Step4: calculate and record $P^z(M_T)$ based on formula(6), if z is max, turn to the next step or turn to the last step;

Step5: calculate $P(O_1,O_t,\cdots O_T)$ based on formula(5);

Step6: let x=x+1;

Step7: calculate and record $P^x(S^x,\sum M^z|\lambda)$ based on formula(8)and(9); if x is max, turn to the next step or turn to the last step;

Step8: calculate and output $\frac{P^x(S^x,M^z|\lambda)}{\sum_{z=1}^{k^{T/\Delta t}} P(M^z{}_T)}$。

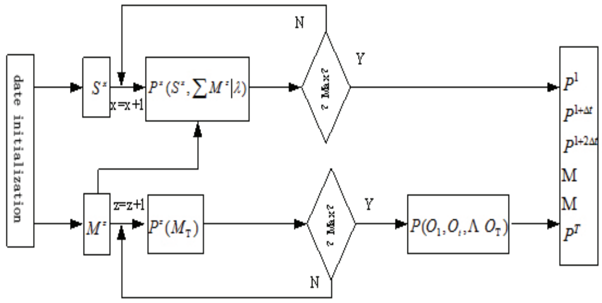

Fig. 1. Driving Condition Prediction Algorithm Process

Model

Select the driving status that get by PERCLOS monitoring method in the synchronization experiment as a comparison of this predicted value, the closer the better. At the same time, the following index is used to assess this early warning capacity of the methods:

$$\Delta AT_P = T_{>PER} - T_P \tag{11}$$

$T_{>PER}$ is the standard value to compare with , which can be regard as the actual time of a driving status to abnormal status. T_P is the predicting time in which the abnormal driving status probability is more than $P\%$. ΔAT_P can be used to evaluate early warning time difference when the prediction threshold is $P\%$.

Simulation Examples

Use the data of reference [13] as samples to analysis the model. Normalized sample data is shown in Figure 2. By clustering the status can be divided into 12 statuses. Let $O_t = O_t(\Delta v < 0.15 \; and \; v < 0.94 \; and \; d < 0.57)$, the observed status of M^z can be constructed, including (O_1,O_2,O_3,O_4,O_6). The former 300 data are used as HMM network training data, and the last 50 data are used to text. Prediction step is 1 and a set number of steps are 60. The text results of abnormal driving status prediction are shown in Figure 3. Figure 3 (a) is the detection results of the PERCLOSE, and Figure 3 (b) is the prediction results of this paper.

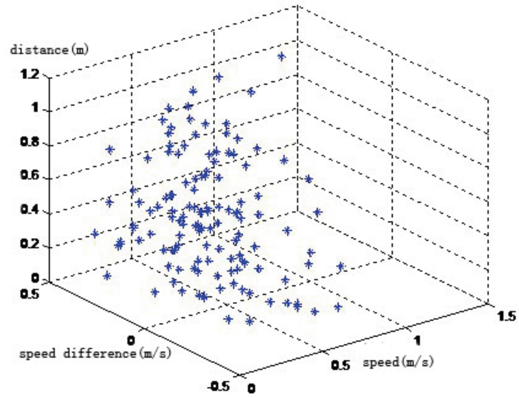

Fig. 2. Observe Variable Samples

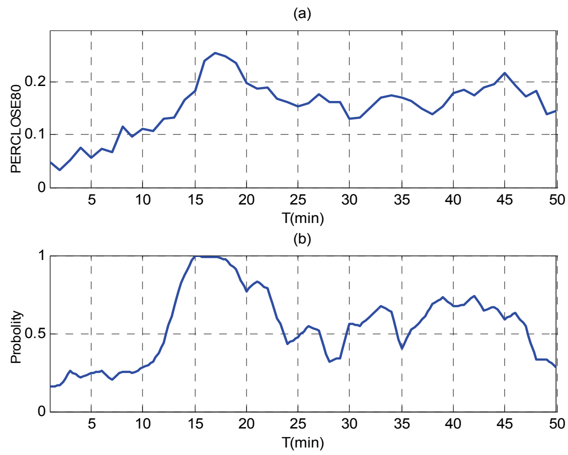

Fig. 3. Predicting Results Compared and Analysis

Figure 3 shows that: (1)abnormal driving status trends predicted in the paper are consistent with the PERCLOSE monitoring, which means that the proposed method is correct, and the changing process of driving status can be reflected. (2)in the test data, the first appearance of the abnormal driving status is $T_{>PER} = 13\min 54s$ based on the method PERCLOSE, but the predict time is earlier than it. When the prediction threshold $P\%$ is different, the degree of advance ΔAT_P is different: when $P\% = 30\%, \Delta AT_P = 2\min 7s$;

when $P\%=40\%,\Delta AT_P=1\min 51s$; when $P\%=50\%,\Delta AT_P=56s$, when $P\%=60\%,\Delta AT_P=34s$.

Conclusions

What we can get from the simulation results of this paper is that, based on hidden Markov model basic principles, expressing the physical variable of the vehicle status to achieve the driving status prediction is feasible. The prediction of the driving status trend is consistent with the PERCLOS monitoring, and early warning can be achieved. When $P\%\le 30\%$, it can be more than 2 minutes ahead of time to predict, to provide a more sufficient time for the active safety defense of the Intelligent Transportation Systems. Ministry of Taffic Transportation (2011-319-825-460) .

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