

Highway Traffic Flow Status Recognition Method Based on Deep Neural Network

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Abstract—Expressway traffic flow is an important traffic information of expressway. At present, the main way to detect expressway traffic flow is through video image collection, which is easily affected by external light blocking and has high calculation cost of image analysis. In order to solve the problems of poor accuracy of image analysis and large amount of computation in dynamic image analysis, based on the study of audio signal of expressway traffic, this paper proposed a method of expressway traffic flow status identification based on depth neural network. The method proposed in this paper firstly classifies and defines the traffic flow status, denoises the audio signal and extracts the features, then uses Deep Neural Network (DNN) to build the model to get the DNN model to identify the traffic flow status of expressway, and then pretrains the DNN model. Then the parameters of the model are optimized, and the Hidden Markov Model (HMM) is used to decode the model. Finally, the DNN model is used to estimate the observation probability of audio signals of different expressway traffic flow status, and the result of expressway traffic flow status identification is given according to the calculated probability. The accuracy of the proposed method is compared with that of the existing methods. Experimental results show that the proposed method performs better in recognition accuracy.

Keywords—Deep neural network, Hidden Markov Model, Audio recognition, Smart traffic

I. DEFINE HIGHWAY TRAFFIC FLOW STATUS

This paper classifies and defines the traffic flow status of expressways. The detailed information is shown in Table I. The traffic flow status of expressways is divided into five categories: car-free roads, express roads, normal roads, busy roads, and blocked roads. Among them, the speed of the car-free lane is 70Km/h and above, the speed of the express lane is 60-70Km/h, the speed of the normal lane is 40-60Km/h, and the speed of the busy lane is 20-40Km/h. The speed of blocked lane is 0-20Km/h.

Audio signal of expressway traffic contains different sound signals. In busy or congested expressway, this paper focuses on different sounds, such as engine idle sound, horn sound and so on. However, on a car-free highway, the focus of this paper is on air turbulence and other environmental sounds. These sounds are collected in audio signals of expressway traffic and can be

expressed in the form of features further classified into various traffic flow status.

TABLE I. TRAFFIC FLOW STATUS INFORMATION TABLE

Number	Traffic flow status	Speed (Km/h)
1	car-free roads	70 and above
2	express roads	60-70
3	Normal roads	40-60
4	Busy roads	20-40
5	Blocked roads	0-20

II. PROCESSING AUDIO SIGNAL OF EXPRESSWAY AND ITS MECHANISM MODELING AUDIO SIGNAL

In this paper, the audio noise reduction algorithm based on wavelet transform is used to remove the background interference in the audio and enhance the audio signal of highway traffic. Then the audio signal of highway traffic is replaced by EMD decomposition, and the MFCC feature based on classical modal decomposition weighting is utilized. Finally, we can obtain the characteristic parameters of the audio signal MFCC of the highway traffic, and realizes the processing of the audio signal.

The audio signal of highway traffic belongs to a time series signal. Before using Deep Neural Network (DNN) for modeling, the audio signal needs to be controlled in length because the input of the DNN is fixed. This paper proposes a highway traffic flow status recognition method based on deep neural network. In this method, DNN is used to estimate the observation probability of audio signals of different highway traffic flow status. The observation sequence is given. By training the DNN to estimate the state posterior probability of the continuous density HMM, the network structure output obtains the posterior probability, and the Restricted Boltzmann Machine (RBM) superposition constitutes the DNN model, forming a bottom-up distinction. The sexual training model uses supervised training to transfer the errors between the layers from bottom to top; the RBM structure includes the visible layer and the hidden layer; the visible layer contains random nodes, and the hidden layer

contains binary random nodes; supervised training is used to transfer the error between layers; the RBM structure includes the visible layer and the hidden layer; the visible layer contains random nodes, and the hidden layer contains binary random nodes.

The extracted audio signal characteristic parameters of the highway traffic flow status are used as input data of the DNN model, and the Gaussian model is used to model the cells in the visible layer of the RBM structure, and the hidden layer obeys the Bernoulli distribution. The energy function is as follows:

$$E(x, y | \theta) = \sum_{i=1}^x (x_i - a_i)^2 - \sum_{i=1}^x \sum_{j=1}^y x_i w_{ij} y_j - \sum_{j=1}^y b_j y_j \quad (1)$$

The parameter x 、 y 、 θ respectively represent the number of visible layers in the RBM structure, the number of hidden layers, and the parameter set of a single RBM; the parameter set θ includes parameters a_i, b_j, w_{ij} , a_i representing the offset of the first visible layer, x_i represents the visible layer vector, and y_j represents the hidden layer. b_j representing the offset of the j hidden layer, w_{ij} representing the connection weight of the visible layer i and the hidden layer j .

In this DNN model structure, there are connections between the layers of RBM, but there are no connections within each layer. Under the premise that the nodes in the visible layer are known, the states of each node in the hidden layer are independent of each other. Under the premise that the nodes in the visible layer are known, the activation probability of the j node in the hidden layer is calculated as shown in Formula 2. Similarly, if the nodes of the hidden layer are known, the activation probability of the i node of the visible layer is calculated as shown in Formula 3.

$$P(y_j = 1 | x, \theta) = \frac{1}{1 + e^{-(b_j + \sum_i x_i w_{ij})}} \quad (2)$$

$$P(x_i = 1 | y, \theta) = \frac{1}{1 + e^{-(a_i + \sum_j y_j w_{ij})}} \quad (3)$$

III. DEEP NEURAL NETWORK MODEL FOR TRAFFIC FLOW STATE IDENTIFICATION OF PRE-TRAINED EXPRESSWAY

In the expressway traffic flow status identification model, the pre-training of DNN is mainly to train multi-layer RBM. One layer of RBM is completed, and the other layer of RBM can be used to represent the data. Given the vector x , the activation vector y of the hidden layer node can be calculated, and the hidden layer vector of RBM is used as training data to train the RBM of the other layer. Therefore, the weights of the next layer RBM are obtained by extracting the features from the output results of the previous layer. After RBM stops training, Deep Belief Networks (DBN) with the same number of layers as RBM are obtained, and the weight coefficients of each layer of RBM correspond to the initial values of each layer of DBN. Therefore, the parameters in the DBN network can be tuned after DBN initialization.

The weight of each DBN layer is taken as the initial weight of the DNN with Sigmoid function as the active unit, which is labeled in the DNN structure. After the pre-training of the DNN, a layer of randomly initialized Softmax is introduced as the output layer, and the DNN weight parameters are adjusted by back propagation algorithm. For a hidden layer in the DNN model $0 < l < L$, the input data is the output result vector of the visible layer of the upper layer x_{l-1} . The nodes in the hidden layer are independent of each other, and the Equation for calculating the conditional probability is shown in Equation 5. The Equation for calculating the conditional probability of the label corresponding to the output layer thereof is shown in Equation 6;

$$P(y_l | x_{l-1}) = \sigma(x_{l-1} \bullet W_l + b_l) \quad (5)$$

$$P(h | x_{l-1}) = \text{softmax}(x_{l-1} \bullet W_L + b_L) \quad (6)$$

b_j represents the offset of the j hidden layer, W_l represents the connection weight of the l layer hidden layer and its corresponding visible layer.

The pre-training method can improve the performance of DNN in the process of testing after initializing the weights of DNN. The initial state of the network model during training has an impact on the performance of the final model. At that same time, the model parameter are adjusted by back propagation algorithm when the model is pre-train; Finally, the data in the pre-training process can be untagged, and untagged data is used in the pre-training phase, which reduces the computational burden.

IV. PARAMETER OPTIMIZATION OF IDENTIFICATION MODEL

After the DBN and initial weights are obtained, back propagation algorithm is used to optimize the parameters of DNN network. In the process of parameter tuning, each frame is marked with its own category. In this paper, the cross entropy objective function is used to adjust the network parameters to minimize the loss between the training objective and the hypothesis class.

For the observation vector is $O = \{o_1, o_2, \dots, o_n\}$, the output class of neurons is $q \in \{1, \dots, C\}$, $C = N_L$ is the number of classes, which is the traffic flow status class of expressway. The probability that the observation variable o is category i is $P_{dnn}(q|o)$, that is, the value of the i output of the output layer x_i^L . The output vector x^L is obtained by normalizing the Softmax function satisfying the conditions $v_i^L \geq 0$ $\sum_i x_i^L = 1$, and belonging to a multi-term probability distribution. The calculation method is as follows:

$$x_i^L = P_{dnn}(q|o) = \text{softmax}_i(z^L) = e^{z_i^L} / \sum_{j=1}^C e^{z_j^L} \quad (7)$$

After determining the observation vector $O = \{o_1, o_2, \dots, o_n\}$, the DNN model calculates the output of the network structure

layer by layer through forward calculation, which is calculated by the parameters $\theta = \{W^l, b^l \mid 0 < l < L\}$. In the expressway traffic flow identification model, the objective function of network structure optimization is calculated as follows: after the objective function is derived, the network structure parameters are adjusted by back propagation algorithm;

$$J(W, b) = -\frac{1}{M} \sum_{m=1}^M \sum_{q=1}^C v_i^m \log x_i^L \quad (8)$$

Where W is the connection weight of the visible layer and the hidden layer, M is the characteristic parameter of the observation vector, v_i^m is the observation sequence, x_i^L is the posterior probability of the DNN calculated by Equation 7, and v_i is calculated by the indicator function $v_i = I(c = i)$, as shown in the following formula:

$$I(x) = \begin{cases} 1, & \text{true} \\ 0, & \text{other} \end{cases} \quad (9)$$

V. DECODING STATE RECOGNITION MODEL USING HIDDEN MARKOV MODEL

Because the audio signals of different expressway traffic flow statuses interact with each other, for example, there are similar components in the audio signal components of busy status and blocked status, it is necessary to distinguish the similar components in different states when modeling the audio signal data. As a result, models that are less capable of modeling may not be able to distinguish such differences well. Depth neural network can be used to solve the classification problem well. In estimating the observation probability, depth neural network takes into account the characteristics of audio signals in different states, obtains a high-dimensional feature vector with high discrimination ability, and obtains a more reasonable probability distribution. The training algorithm of expressway traffic flow status identification model based on DNN-HMM is shown in algorithm 1.

In this paper, the depth neural network is used in the model of expressway traffic flow status identification, and the training process is to use labeled data for supervised training. Therefore, step (4) of the algorithm needs a stable GMM-HMM model to sort the training set data and obtain the labeled training set data. In step (7) of the algorithm, when the training process does not reach convergence, continue to use DNN-HMM to sort the training set data, and iteratively train the depth neural network until the algorithm reaches convergence.

After the training of expressway traffic flow status identification model based on DNN-HMM is completed, the HMM decoding part of expressway traffic flow status identification model based on DNN-HMM is carried out. In this process, the probability is calculated, not the value of posteriori probability, so the transformation calculation is needed through Equation 10.

Algorithm 1 Highway traffic flow status recognition model base on DNN-HMM training algorithm

Input: Audio signal observation sequence

Output: Probability $p(s_t)$

DEFINE:

A : Implicit state transition probability matrix of HMM

B : Observation state transition probability matrix of HMM

N : HMM status

BEGIN

(1) Train a state-shared GMM-HMM highway traffic flow status recognition model, the sharing state is determined by the decision tree, and the model obtained after training is set to $gmm-hmm$

(2) Use $gmm-hmm$ to initialize the hidden Markov model, set the parameter value of $\lambda = (A, B, N)$, and obtain the DNN-HMM-based highway traffic flow status recognition model set to $dnn-hmm_1$.

(3) Pre-training the deep neural network of $dnn-hmm_1$, and obtaining the deep neural network after training is set to dnn_{pre} .

(4) Use $gmm-hmm$ to arrange the training set, calculate the hidden Markov state corresponding to the training set data, and obtain the data set to H .

(5) Adjust the parameters of dnn_{pre} by H , and use the back propagation algorithm to obtain a new deep neural network set to dnn_{new} .

(6) Re-estimate the transition probability and observation probability parameters in HMM through $dnn-hmm_1$ and dnn_{new} , and use the maximum likelihood similarity algorithm to obtain a new deep neural network set to dnn_{sec} .

(7) The training set data is rearranged by dnn_{new} and dnn_{sec} , and the process returns to step (5); until the result of the result of (6) is not improved, the algorithm is exited.

(8) Give the training set data and estimate the probability value $p(s_t)$

END

$$p(o_t | s_t) = \frac{p(s_t | o_t) p(o_t)}{p(s_t)} \quad (10)$$

In the above equation, s represents a sequence of unobservable states in the hidden Markov model, $p(s) = T_s / T$ represents a priori probabilities of different states derived from the training set, T_s represents frame values whose states are labeled S , and T represents the total frame values of the training set. This method can reduce the error of label, but it can not improve the recognition accuracy under some conditions. As that a priori probability value $p(s_t)$ is obtain from the training set, the probability value $p(o_t)$ has no effect on the final recognition result, When using the depth neural network

to estimate the probability value $P(s_i | o_i)$, the state of each hidden Markov model corresponds to the same signal depth neural network, which increases the number of nodes in the output layer and the corresponding number of nodes in the hidden layer, and ensures the modeling ability of the expressway traffic flow status identification model.

Finally, the DNN model is used to estimate the observation probability of audio signals of different expressway traffic flow status, and the result of expressway traffic flow status identification is given according to the calculated probability.

□.EXPERIMENTAL RESULTS AND ANALYSIS

A. lab environment

This experiment uses MATLAB software to carry on the experiment simulation, the software runs on the HPZ820 workstation, the workstation performance detailed parameter is shown in Table II, the programming simulation software is MATLAB 2012 version. The audio data of the experiment are recorded live on outdoor roads, and the environment is normal weather (excluding rain and snow weather). The collection time is from 08:00 to 19:00. These audio data cover five traffic flow status: car-free road, express road, normal road, busy road and blocked road. The data label is mainly used to label the traffic flow status manually.

TABLE II. WORKSTATION PERFORMANCE PARAMETERS TABLE

Performance	Performance parameter
CPU type	Quad-core Xeon E5-2603
CPU frequency	1.8GHz
CPU thread	number 24 threads
Memory Type	DDR3-1333 ECC
Memory capacity	8GB
Hard disk type	15000 rpm SAS hard disk
Hard disk capacity	300GB
Bandwidth	1000Mbps

All audio data is first converted into wav format audio at a sample rate of 48 KHz mono via Cool Edit Pro 2.0, an audio editing software. All audio data are divided into two sets, one is training set and the other is test set. The training set data is used to train the model parameters, and the test set data is used to classify and identify the model parameters. There are 400 samples in the training set, and the number of audio data samples of non-vehicular roads, expressways, normal roads, busy roads and blocked roads are all 80. There are 200 samples in the test set, and the number of audio data samples of car-free roads, express roads, normal roads, busy roads and blocked roads are all 40.

In the test phase, a section of audio data of known expressway traffic flow status is input, noise is reduced, and then the feature vectors are extracted to construct the feature vector set of audio signal of expressway traffic flow status, which is then input into the trained expressway traffic flow status recognition model based on DNN-HMM. The

recognition model gives the recognition result of the audio data to be recognized, and determines whether the recognition result of the recognition model is correct by referring to the known category information, and records the result; Finally, the accuracy of the statistical recognition results is measured by the recognition accuracy, which is calculated as shown in Equation 11:

$$P = \frac{C}{S} \times 100\% \quad (11)$$

Among them, P stands for classification accuracy, C stands for the correct number of samples, and S stands for the total number of samples.

B. Experimental results and analysis

1) **Data usage and learning rate impact:** As can be seen from the foregoing, the DNN training algorithm based on random data selection determines the utilization rate of training data by selection function. FIG.1 shows the recognition error rates corresponding to three different selection functions under different data usage rates. The analysis shows that when the data usage rate is lower than 77%, the recognition performance is greatly degraded by the T_1 selection function. T_2 selection function also degrades the recognition performance, but it is better than T_1 selection function. When the data usage rate is 56%, the error rate of T_3 selection function is 25.3%, and the model recognition performance is the best. T_3 selection function is used in the following experiments.

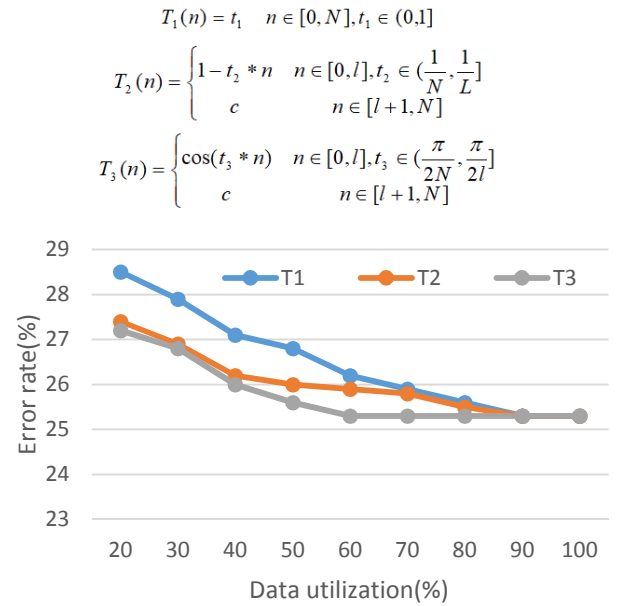


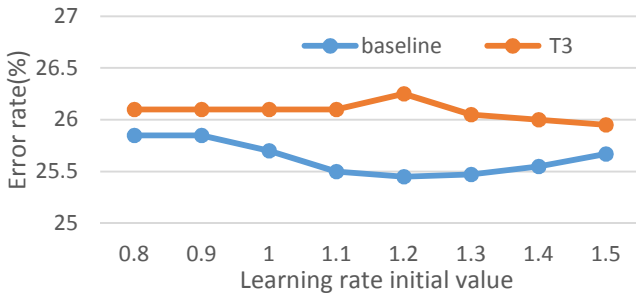
Fig. 1 The relationship between performance and data usage rate of 3 sweeping functions

In the training process of expressway traffic flow status identification model based on DNN-HMM, the training process of DNN not only passes through the whole training data set every iteration, but also constantly changes the learning rate. Therefore, it is important to adjust the learning rate

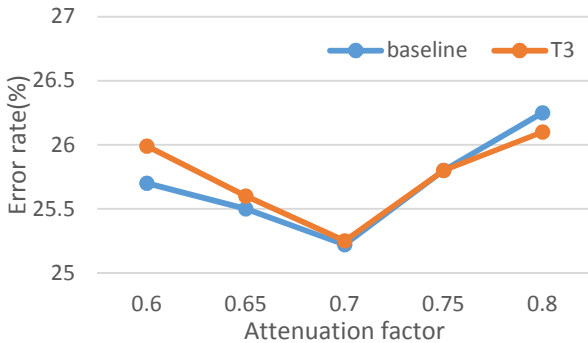
appropriately for the whole training process. Appropriate learning rate adjustment strategy can make the model converge faster. The learning rate γ of different iterative layers in the training process of back propagation is calculated by Equation 12.

$$\gamma(n) = \begin{cases} M & n \in [0, l] \\ \tau^{n-l} M & n \in [l+1, K] \end{cases} \quad (12)$$

In Equation 12, n is the number of iterations, K is the total number of iterations, M is the initial value of the learning rate, l is the layer value when the correct rate of the training set increases below a preset threshold, and τ is the attenuation factor. Below are the effects of learning rates on random data selection. FIG.2 shows a comparison of the performance of random data selection with different initial learning rates and attenuation factors, with the selection function T_3 . Analysis of FIG.2 shows that the performance improvement is relatively small under the condition of larger initial learning rate and attenuation factor. Because different training data are used in each iteration, less training data is used than the overall training data. In order to ensure the overall performance, this paper selected $M=1.5$ and $\tau=0.7$ used in the following experiments.



a) Performance of stochastic data sweeping (T_3) with different initial learning rates



b) Performance of stochastic data sweeping (T_3) with different decaying factors and initial learning rate=1.5

Fig. 2 Performance of stochastic data sweeping (T_3) with different initial learning rates and decaying factors

2) Test and Verification of Highway Traffic flow status

Recognition Model: In this experiment, the multi-audio signal denoising algorithm based on wavelet transform is used to denoise the expressway, Then the MFCC feature extraction

algorithm based on classical modal decomposition weighting is used to extract the feature parameters, The 13-dimensional MFCC parameters, the first-order difference parameters and the second-order difference parameters are combined to form the eigenvector. As the input parameters of the DNN-HMM-based expressway traffic flow status identification model, the number of input layer is 1, the number of input layer nodes is 429 ($39 \times 11 = 429$), the number of hidden layer nodes is 3, the number of each hidden layer node is 1024, and the number of output layer is 1.

According to the audio signal characteristics of different expressway traffic flow status, 400 training sample data were selected, 80 audio data of each expressway traffic flow status were used to build the DNN-HMM model base. Contrast divergence algorithm is used to construct the DNN model, and back propagation algorithm is used to pre-train the DNN model. A DNN training algorithm based on random data selection is proposed to optimize the parameters of back propagation algorithm to train the DNN model, reduce the number of training samples and shorten the iteration time. HMM decode calculation in DNN-HMM is carried out, that probability value of observation sequence is obtain, and the recognition result is obtained.

Two hundred test data were used to test the performance of expressway traffic flow status identification model based on DNN-HMM. There are 40 audio data for each traffic flow status. FIG. 3 shows an accuracy result of expressway traffic flow status identification based on DNN-HMM. As can be seen from FIG. 3, the identification rate of busy roads is lower because the audio signal of busy roads contains both the audio signal of normal roads and the audio signal of congested roads; However, the accuracy of lane identification is higher for non-traffic lanes and congested lanes, mainly because the audio signals of these two traffic flows are more distinctive.

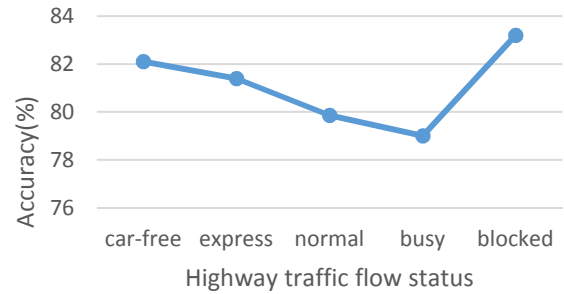


Fig3 Accuracy of highway traffic flow status recognition based on DNN-HMM

3) Comparative analysis of the proposed method and existing methods: Support vector machine (SVM) is a widely used classifier model in the current traffic flow status recognition research. In order to study the superiority of the proposed method of expressway large-scale vehicle recognition based on depth neural network, the DNN-HMM-based expressway traffic flow status recognition model and support vector machine model proposed in this paper are

compared and the experimental results are analyzed. The kernel and kernel functions of SVM are shown in Table III. The SVM models with different kernel functions are tested to determine the SVM model. The support vector machine models with different kernel functions are trained by the audio signal training set data of expressway traffic flow status, and the trained models are verified by the test set data.

TABLE III. SVM KERNELS AND KERNEL FUNCTIONS

Number	kernel	kernel functions
1	Linear	$K(x, x_i) = x_i^T x$
2	Secondary	$K(x, x_i) = (x \bullet x_i^T + 1)^2$
3	Polynomial	$K(x, x_i) = (x \bullet x_i^T + 1)^d$
4	RBF	$K(x, x_i) = \exp(-\gamma \ x - x_i\ ^2)$
5	MLP	$K(x, x_i) = \tanh(\kappa \bullet x x_i^T x x_i^T + \theta)$

In order to extract the characteristic parameters of MFCC and frame windowing for the audio signals of five kinds of expressway traffic flow state, the characteristic vectors of the extracted audio signals of five kinds of expressway traffic flow state are trained as the input of support vector machine, and the support vector machine model of expressway traffic flow state is obtained. Then the performance of support vector machine model is validated. The performance experiments of support vector machine models with different kernel functions are carried out respectively. 200 test data are used to test the performance of support vector machine model. The test results are shown in Fig.4.

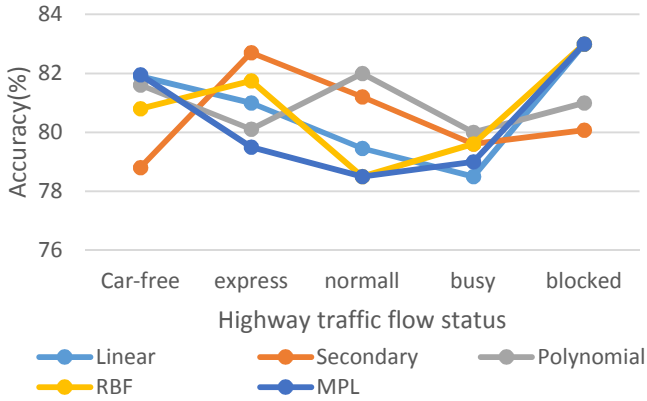


Fig. 4 Accuracies of highway traffic flow status recognition based on SVM

The performance information of expressway traffic flow status recognition model based on DNN-HMM and SVM model with different kernel functions is summarized in Table IV. The analysis of Table IV shows that the accuracy of each model is lower because the audio signal of busy road contains

support vector machine model. As can be seen from that analysis of the content of Table IV, the identification accuracy of each model for the busy road is low, because the audio signal of the busy road contains the audio signal of the normal road as well as the audio signal of the congested road; The comprehensive recognition rate of SVM models with different kernel functions is compared and analyzed. The performance of SVM with polynomial kernel function is the best, and the comprehensive recognition rate is 80.93%. The comprehensive recognition rate of expressway traffic flow state recognition model based on DNN-HMM is 81.058%, which is better than that of SVM with polynomial kernel function.

TABLE IV. ACCURACIES OF HIGHWAY TRAFFIC FLOW STATUS RECOGNITION BASED ON SVM

Model	Car-free	Express	Normal	Busy	Blocked	Comprehensive recognition rate
Linear-SVM	81.76	81.03	79.4	78.5	82.9	80.72
Secondary-SVM	78.63	82.6	81.3	79.5	80.1	80.43
Polynomial-SVM	81.54	80.23	81.96	79.9	81.0	80.93
RBF-SVM	80.7	81.6	78.4	79.5	83	80.64
MPL-SVM	81.86	79.5	78.34	78.9	82.9	80.32
DNN-HMM	82.1	81.37	79.74	78.9	83.2	81.06

VII CONCLUSIONS

This paper mainly introduces the expressway traffic flow state identification method based on DNN-HMM, and introduces the identification process and algorithm of this model. The DNN training algorithm based on random data selection is proposed, which reduces the number of training data and shortens the training time when the model parameters are adjusted by Back Propagation (BP) algorithm. The training algorithm of expressway traffic flow state identification model based on DNN-HMM is proposed to calculate the probability and get the identification result. Finally, the validity and accuracy of the model are verified by experiments, and the learning rate and attenuation factor are determined by comparing the model recognition performance of different selection functions in DNN training algorithm based on random data selection. The DNN-HMM model under different expressway flow state is constructed and validated based on the DNN-HMM model. The accuracy of the proposed method is compared with that of the existing methods. Experimental

results show that the proposed method performs better in recognition accuracy. Therefore, the method based on

DNN-HMM is feasible and effective in expressway traffic flow state recognition.

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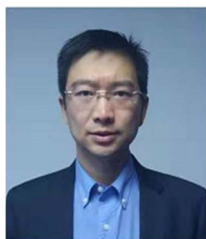
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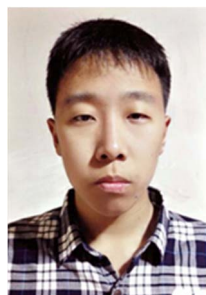
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