Short-term Vehicle Speed Prediction by Time Series Neural Network in High Altitude Areas

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Abstract. Vehicle driving conditions at high altitudes are quite different from those in plain areas. Accurately predicting the speed of vehicles traveling at high altitudes is of great significance for the development of vehicle safety assisted driving. In order to study the vehicles’ speed of highways in high-altitude areas, and predict the speed of vehicles accurately, more than 30 000 data were collected by a medium-sized SUV in Qinghai under typical adverse environmental conditions. The real-time vehicle status data (engine speed, engine torque, transmission gear, throttle opening), road alignment data, and historical vehicle speed data was denoised by wavelet method. The collecting data is time-varying and nonlinear characteristics. A nonlinear auto-regression with exogenous inputs (NARX) dynamic neural network prediction model was established in this paper to fit travel speed. The network model after training has small error and high fitting degree. The accuracy of vehicle speed prediction in the next five seconds is 96.01\%. The root mean square error of prediction is less than 2.21 km/h, which can achieve better prediction effect. At the same time, the transplantability of the model is enhanced by taking altitude and road alignment as variables.

1. Introduction

Because of the influence of human, vehicle, road, environment and other natural and human factors, the trajectory of speed has the characteristics of time-varying, complexity and height uncertainty, which greatly increases the complexity and difficulty of speed time series prediction\cite{1}. The research methods
proposed by scholars for vehicle speed prediction can be divided into two categories: physical model-based method and data model-based method [2]. Among the physical model-based methods, most of them are about vehicle dynamics model and aerodynamics model. For example, J. Kristinsson et al. [3] based on the traffic data measured on expressway, proposed an aerodynamic traffic model to predict the vehicle speed for 5 minutes and 10 minutes in a certain section of a road; D. Ngoduy [4] proposed an extended multi-stage aerodynamic theory for vehicle mixed traffic flow to predict the vehicle speed, and established a multi-class macro-model on the ring expressway. The numerical simulation of the model is validated. Because of the remarkable time-varying and non-linear characteristics of vehicle speed data, the prediction of vehicle speed based on physical model has great limitations.

The methods based on data model focus on the use of current and past data, and gives little consideration to complex physical models, such as neural networks, nonparametric regression models, hidden Markov model and Kalman filtering algorithm. Speed prediction based on mathematical model mainly focuses on road alignment design[5-8], traffic flow forecasting[9-11], automobile navigation[12 -14] and so on, but there are relatively few literatures focusing on speed prediction.

In terms of the application of hidden Markov model, Chien-Chuan Lin et al. [15] predicted and judged the changing trend of vehicle speed by using the driving data recorded by digital cameras, through the combination of digital image analysis, feature detection and hidden Markov model. Wang Mingxi et al. [16] Established a single camera vehicle speed prediction model based on image feature detection and hidden Markov model to predict vehicle speed in the next 1.5 seconds.

Xie Shaobo et al.[19] established four prediction models of linear regression, polynomial regression, BP neural network and fuzzy neural network to predict the vehicle speed under linear conditions of different sections. Based on support vector machine (SVM) and neural network method, B. Jiang et al.[20] used the combination of neural network and fuzzy neural network to predict the speed of vehicles on the road. Fu Jia[21] used the vehicle speed GPS to collect the vehicle speed information, and used BP neural network algorithm to predict the average speed of the bus every half hour. Xie Hao[22] based on BP neural network method to establish a vehicle speed prediction model, using particle swarm optimization algorithm and genetic algorithm to optimize the established vehicle speed prediction model. Yuan Lushan[23] predicted the vehicle's next second speed based on the NAR neural network and applied it to the anti-collision warning system. Li jianyuan[7] et al. established the neural network relationship model between vehicle speed and plane linear elements based on the artificial neural network.

Li Jinyan et al. [24] established a multi-step prediction model based on Kalman filter algorithm, and optimized the model by synthetically utilizing prediction data, historical data and real-time measurement data. Yang Zhiqing et al. [8] used regression method to obtain a speed prediction model based on spatial visual distance, which can predict the running speed of freeway under the condition of free flow.

The current vehicle speed prediction determines the average vehicle speed or the vehicle speed of a particular road segment. Compared with the vehicle's own speed prediction, although these prediction times are long, the data sampling interval is too large to provide sufficient accuracy for the vehicle decision system. Some vehicle speed prediction models are based on the average speed of a certain section of the space domain, or the average speed of a certain time period based on the time domain, which is not conducive to the application under the premise of accuracy. Although the use of neural network models is relatively large, many do not take into account the time series characteristics of vehicle speed. In addition, when predicting the speed of the highway, there is no reference concerning how to predict the speed of the vehicle in the harsh environmental conditions of the high-altitude area.

In this paper, the CAN bus data of the vehicle including the speed, torque, throttle opening and transmission gear were obtained, which characterize the change of the driving state of the car under high altitude conditions. The analysis is based on the changes of historical speed, road gradient and altitude. And using the feedback and memory function of dynamic neural network, a multivariable nonlinear
autoregressive dynamic neural network vehicle speed prediction model is established to predict the vehicle speed in the next 5 seconds. The model has high prediction accuracy and is of great significance for the development of vehicle safety assisted driving technology such as overspeed safety warning system and vehicle anti-collision warning system.

2. Data collection and processing

2.1. Data collection and screening
The training of the dynamic neural network model requires a large amount of data, so the collection of vehicle speed data is very necessary. A number of sections of Qinghai were selected as test routes for data collection. Finally, the measured data of typical environmentally harsh road sections were selected as the original sample data of this study: the section of Qunke Bus Station in Haidong City, Qinghai Province to the Gucheng Bus Station. The road test date is 2018.07.18, the highest elevation of the road section is 3262.8 m, the maximum solar radiation intensity of the day is 1047.7 W/m², the minimum atmospheric pressure is 63.8 kpa, the lowest air oxygen content is 15.73%, and the highest ambient temperature is 39.4°C.

The test vehicle is a medium-sized SUV equipped with a 4-cylinder supercharged engine and a 5-speed manual transmission. Taking into account the characteristics of data real-time and accuracy, the DEWE data acquisition system is selected to synchronously collect vehicle CAN bus information and GPS information. Among them, the GPS information mainly includes latitude and longitude, altitude and vehicle speed information, etc. The vehicle CAN bus information mainly includes information such as engine speed, engine torque, throttle opening, transmission gear position and the like. The data acquisition system has an acquisition frequency of 1 Hz, and a total of 1551 raw data are collected for the selected road segment, which is used as a raw data sample for network model training and testing after pre-treatment. The distribution of each variable is shown in Table 1.

Table 1 Overview of raw sample data

| variable            | Variable type | maximum  | minimum  | mean     | N     |
|---------------------|---------------|----------|----------|----------|-------|
| altitude/ (m)       | continues     | 3262.80  | 2062.90  | 2626.37  | 1551  |
| torque/ (N·m⁻¹)     | continues     | 222      | 0        | 101.265  | 1551  |
| Rotate speed/ (r·min⁻¹) | continues     | 5 008.5  | 855      | 3469.586 | 1551  |
| gear                | discrete      | 3        | 1        | ----     | 1551  |
| gradient/ (°)       | continues     | 9.842    | 0        | 4.633    | 1551  |
| Throttle percentage/ (%) | continues     | 2.745    | 99.986   | 36.854   | 1551  |
| speed/ (km·h⁻¹)     | continues     | 103.008  | 0.481    | 67.747   | 1551  |

2.2. Noise reduction processing based on wavelet transform
The data collected by the instrumentation is the result of the superposition of real data and various interference noises. Usually with strong volatility, the data violently oscillates and cannot accurately reflect the trend of vehicle speed. Therefore, the original data series needs to be stabilized by the noise filtering method to reduce the error caused by noise. The study compares the noise filtering effects using methods such as mean smoothing, principal component analysis and wavelet transform. The results show that the data noise filtering effect using wavelet transform is better than the mean smoothing method and principal component analysis method, both from the degree of approximation to the original data and the smoothness. Therefore, this paper uses MATLAB's wavelet toolbox to perform noise filtering on the selected original vehicle speed data sequence. In general, the flow of noise reduction processing for a one-dimensional wavelet signal is as shown in Figure 1.
Because Daubechies wavelet has good smoothness and analysis characteristics, this paper uses db4 as the wavelet mother function to denoise the sample vehicle speed data. In the method selection, the noise reduction method of discrete wavelet transform, that is, the threshold processing method is selected, which can effectively extract white noise and reduce the loss of original information. Figure 2 is a 3-layer exploded view of the db4 discrete wavelet of the vehicle speed data. It can be seen from the figure that the data after the noise reduction is closer to the original data s, which can ensure the authenticity of the original signal, which will improve the accuracy of the data prediction.

![Db4 wavelet 3-layer decomposition](image)

Since the noise signal of the data is mainly concentrated in d1, increasing the threshold of the first layer can effectively remove the singular data and achieve the purpose of smoothing the data sequence. The same method is used to perform wavelet reduction processing on the remaining continuous variables, and finally the processed data is derived as sample data.

3. Establishment of NARX neural network vehicle speed prediction model

3.1. NARX Neural Network

The driving speed of a car has high noise, non-stationary and non-linear time series characteristics, so the influence of past inputs and outputs on the current output should be considered when selecting a predictive model. The neural network model is an abstract mathematical model that reflects the brain system and function, and has the characteristics of being able to approximate any nonlinear mapping through training. According to different applications, neural networks can be divided into static neural networks and dynamic neural networks. Static neural networks have no output feedback and no input delay. The output is directly calculated by the input through the forward network. The output of the dynamic neural network is related to the current input and past input and output, so dynamics are usually used in nonlinear systems[25]. The NARX dynamic neural network model is a dynamic recursive network that establishes a model by introducing a delay module and output feedback[26], which introduces output vector delay feedback into network training to form a new input vector. Figure 3 shows the structure of the NARX dynamic neural network model, consisting mainly of the input layer containing the input delay, the hidden layer, and the output layer containing the output delay. u(t) represents the input variable, and y(t) represents the target vector during training. During the training
and testing of the network model, the input of the network model includes not only the original input data but also the trained output data, which greatly improves the generalization ability of the network.

![Figure 3. The structure of NARX dynamic neural network](image)

The mathematical model of the NARX dynamic neural network model can be expressed as shown in equation (1):

\[
y(k) = f(y(k - 1), y(k - 2), \ldots, y(k - n_y), u(k - 1), u(k - 2), \ldots, u(k - n_u))
\]

(1)

Where: \( u(\cdot) \) is the value of the input vector \( u(t) \) at a certain point in time; \( y(\cdot) \) is the value of the target vector \( y(t) \) at a certain point in time; \( n_u (n_u \geq 1) \) is a nonlinear system input order, \( n_y (n_y \geq 1) \) is the output order, and \( n_u \geq n_y \); \( w \) is the weight matrix of the network; \( f \) is the nonlinear function formed during the training process.

### 3.2. Determination of external input variables

In the process of establishing NARX dynamic neural network model, the determination of external input variables is an important link. If the variables are selected properly, the applicability and accuracy of the prediction model will be greatly improved. Because of the incomplete selection of variables in vehicle speed prediction by previous researchers, the prediction effect of the established model is not very ideal, and the dependence on spatial and temporal domains is strong. For this reason, nine indexes such as engine speed \( (X_1) \), transmission gear \( (X_2) \), throttle position \( (X_3) \), road gradient \( (X_4) \), engine torque \( (X_5) \), altitude \( (X_6) \), ambient temperature \( (X_7) \), atmospheric pressure \( (X_8) \), air humidity \( (X_9) \) are selected as the initial external input variables affecting vehicle speed \( (X_0) \). The results of correlation analysis between the above indicators and vehicle speed are shown in Table 2.

| Variable | \( X_1 \) | \( X_2 \) | \( X_3 \) | \( X_4 \) | \( X_5 \) | \( X_6 \) | \( X_7 \) | \( X_8 \) | \( X_9 \) |
|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| Correlation Coefficient | 0.744 | 0.410 | 0.398 | -0.346 | 0.317 | -0.309 | 0.261 | 0.172 | 0.135 |
| Significance Level | 0 | 0 | 0.021 | 0.001 | 0.022 | 0.036 | 0.052 | 0.057 | 0.063 |

Table 2. shows that the first six indicators have significant correlation with vehicle speed \( (X_0) \), while the last three indicators \( X_7, X_8, X_9 \) have weak correlation with vehicle speed \( (X_0) \), so the first six indicators can be formulated as the final external input variables. Among them, altitude \( (X_6) \) is not directly related to vehicle speed, but is significantly related to environmental temperature \( (X_7) \),...
atmospheric pressure ($X_8$) and air humidity ($X_9$), so the correlation between altitude ($X_6$) and vehicle speed can be seen as the cumulative effect of these three indicators on vehicle speed.

Because the change of vehicle speed lags behind the change of vehicle state parameters such as $X_1$, $X_2$, $X_3$, $X_5$ and external environment parameters such as $X_4$, $X_6$, etc., it is reasonable to choose as the external input variable. At the same time, because the neural network can apply the factors such as road roughness and driver's response under different driving conditions as invariable factors to the subsequent prediction, it can make the network model learn and memorize driver's driving habits well, thus reducing the influence of the differences between drivers and road sections. Because the influence of road alignment and elevation changing with time is also considered, the dependence of network model on road sections is reduced, and the generalization of practical application is enhanced.

3.3. NARX neural network structure design

The sample data used in this paper is a set of vehicle speed data, engine state data (engine speed, engine torque, transmission gear position, throttle opening) and road line data after a wavelet denoising process with a duration of 1551 seconds and a sampling interval of 1 second. The data is grouped into: the first 1521 data as training data and verification data, and the last 30 data as inspection data. The training data is used to adjust the weight and threshold of the network, the verification data is used to minimize the over-fitting phenomenon in the training process, and the test data is used to verify the prediction effect of the network structure. The test of generalization ability should use sample data other than training data. When the error of network training is very small and the error of verification data begins to increase, it indicates that the generalization performance of network training is optimal[22].

The neural network hidden layer activation function uses a tansig tangent function, and the output layer activation function uses a purelin transfer function. The network is evaluated based on mean square error (MSE) and root mean square error (RMSE), where $N$ is the set of networks to predict future steps.

\[
MSE = \frac{1}{N} \sum_{t=1}^{N} (X_t^* - X_t)^2 \tag{2}
\]

\[
RMSE = \left( \frac{1}{N} \sum_{t=1}^{N} (X_t^* - X_t)^2 \right)^{1/2} \tag{3}
\]

In order to achieve the expected prediction effect, it is necessary to continuously filter the network structure of the NARX dynamic neural network model. When designing the neural network model structure, increasing the number of hidden layers can improve the performance of the model, but at the same time, the calculation amount of the model will increase, which greatly increases the training time and even affects the stability of the entire network model structure. Because the artificial neural network with one layer of hidden layer can approximate arbitrary functions, it fully meets the training requirements[27]. For improving the accuracy of the network model, increasing the number of hidden layer neurons is simpler in terms of structural implementation than adding hidden layers. Therefore, this paper uses a layer of hidden layers to optimize the network by adjusting the number of neurons in the layer.

When the number of hidden layer neurons and the delay order of the network model are increased, the network performance increases first and then decreases, which indicates that under the current sampling interval, the change of the future vehicle speed is less correlated with the earliest sampling speed, and the excessive number of neurons in the hidden layer will cause the network model to learn the noise of the data and over-fitting. In this paper, the trial output method is used to determine that the output delay of the network is 5, the feedback delay is 5, and the number of hidden layer neurons is 15. The network model established at this time is the best.

4. Experimental results and analysis

To verify the rationality and effectiveness of the established neural network model, run the model and analyse the final output. The training and prediction results of the network model are shown in Figure
4, 5 and 6. The last 30 data are time series trajectories of predicted vehicle speed data and sample vehicle speed data.

Figure 4. NARX neural network training effect chart

Figure 5. NARX neural network training and prediction renderings
Figure 6. Prediction error map of NARX neural network model

It can be seen from Figure 4, Figure 5 and Figure 6 that the trained neural network can express the vehicle speed data very well. When the number of training reaches the 14th time, the error is the smallest, and the mean square error of the whole data set tends to $10^{-4}$. Except for a few unique points, the absolute error of the overall prediction is between $[-1, 1]$ and the relative error is also within 2%. Therefore, the network model established has achieved the expected effect, and the accuracy of predicting the vehicle's own vehicle speed is greatly improved compared with other researchers, and can be well used to predict the vehicle speed time series.

The above prediction of the next-time vehicle speed is only for predicting the vehicle speed in the next second. If the vehicle speed in the second second is predicted directly, since there is only the predicted vehicle speed of the next second output feedback and there is no external input variable corresponding to the next second, the historical available data of the network model for vehicle speed prediction is incomplete. As a result, the prediction error becomes very large. Therefore, when predicting the speed of the second second, third second, respectively... in the future, the speed data of the time series and the value of the external input variable, which are separated by 1 second, 2 seconds, respectively...from the original vehicle speed sample data, are taken to establish corresponding sample data sets $L_2$, $L_3$, ... At this time, the prediction of the vehicle speed at the next moment is the prediction of the vehicle speed in second second, the third second... Due to the significant time-varying and nonlinear characteristics of the vehicle speed time series data, and the smaller the sample vehicle speed database selected as the interval becomes longer, the influence on the training and prediction accuracy of the established multivariate NARX dynamic neural network model becomes larger. In this paper, only the vehicle speed in the next 7 seconds is predicted, and the error statistics under different prediction durations are shown in Table 3.

| Delay order | MSE     | RMSE    | MSE     | RMSE    | MSE     | RMSE    | MSE     | RMSE    |
|-------------|---------|---------|---------|---------|---------|---------|---------|---------|
| 4           | 0.62084 | 0.21578 | 0.33472 | 0.15844 | 0.73600 | 0.23495 |        |         |
| Forecast duration/ (s) | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 4           | 12.81730 | 1.67734 | 32.63542 | 1.56450 | 37.26423 | 1.88773 |        |         |
| 5           | 47.01862 | 1.87787 | 65.01114 | 2.20813 | 47.51368 | 2.82908 |        |         |
| 6           | 85.87859 | 2.53789 | 164.33612 | 3.51073 | 106.71621 | 3.17293 |        |         |
| 7           | 160.29311 | 3.46727 | 221.63310 | 4.07707 | 134.23306 | 3.62279 |        |         |

It can be seen from Table 2 that when the delay order is 5, the multivariate NARX dynamic neural network model has a better prediction effect on the vehicle speed time series as a whole. As the error of the prediction time increases, the error increases from the 5th second. It shows that the correlation between the speed of the first four moments and the speed of the next moment has changed greatly when the sample data set is established at intervals of 4 seconds. The root mean square error of predicting the vehicle speed in the next 5 seconds is within 2.21 km/h, which has achieved good expected results. In order to ensure the prediction accuracy, only the vehicle speed in the next 5 seconds is predicted. The data also shows that the multivariate NARX dynamic neural network model can predict the time series of the vehicle speed on the highway in high altitude areas for a period of time in the future. And when the historical sample vehicle speed data is sufficient, the prediction accuracy and prediction duration will be improved. However, when the prediction time is long, the historical vehicle speed sequence data has little correlation with the vehicle speed to be predicted, and it is also affected by the uncontrollable factors such as the driver, the external environment and other vehicles, which leads to the deterioration of the prediction effect of the network model.

5. Conclusion
In this paper, the time series prediction of vehicle speed for a period of time on highway in high altitude area is taken as the research object. By processing and analyzing the time series data of vehicle speed collected from road measurement, combining the data collected from vehicle CAN bus and vehicle GPS, the self-learning ability of non-linear autoregressive (NARX) dynamic neural network is used to establish the prediction model of vehicle speed. Preliminary research progress has been made.

- Using the measured data of the road as a sample database to predict the time series of the vehicle in real time, and verify that the multivariable NARX dynamic neural network model can predict the speed time series of the car for a period of time
- Introducing the road linear data as an external variable, and solving the current research on the vehicle's own speed prediction, the prediction model has strong dependence on the road environment, poor portability and poor generalization ability.
- The altitude change is introduced as an external variable, and the working conditions of such a vehicle in a high-altitude area are studied, which make up for the shortcomings of other researchers' speed-time series prediction models that are only effective for low-altitude conditions and not applicable to high-altitude conditions.
- Because the introduction of vehicle CAN bus data as an external input variable enables the network model to learn and memorize drivers' driving habits, the accuracy of vehicle speed prediction in the next five seconds will be greatly improved to 96.01%, which is better than that of the NAR neural network model in reference [23]. At the same time, on the premise of guaranteeing the prediction accuracy, the prediction time delay of vehicle speed time series has been improved to a certain extent compared with the prediction based on hidden Markov model in reference [15].

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