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Special Focus on Driver Automation Collaboration and Augmentation in Automated Driving

Investigating long-term vehicle speed prediction based on GA-BP algorithms and the road-traffic environment

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Dear editor,

Effective and accurate long-term speed prediction is crucial for intelligent transportation and automobile intelligent energy management systems of intelligent connected vehicles. These predictions have important research value and broad application prospects including widespread use in improving traffic efficiency and safety, fuel economy, remaining driving range estimation [1], and electric vehicle energy management [2,3]. A novel method for long-term speed prediction that aims to build a mapping model between the driver-vehicle-road-traffic characteristic parameters and vehicle speed is proposed in this study. The contributions of this study are as follows. (1) The main factors influencing vehicle speed are quantified and nonlinear mapping relationship is explored using GA-BP algorithms, which can enhance the accuracy and robustness of speed predictions for different road types. (2) Using driving data of individual drivers for training the model better reflects individual driving habits, which is advantageous for intelligent energy management and control of individual vehicles.

Constructing the road-traffic environment characteristic vector. (a) The road type, categorized primarily into urban, suburban, and expressway roads, is identified and speed limit is obtained by inputting a starting point on the map.

(b) The traffic state of each section is described using the average speed and speed distribution. Meanwhile, other characteristics such as the lane number, crossing intersection setting, traffic signals, and vehicle location information are also considered and described.

Algorithm principle. In this study, the nonlinear mapping relationship between the characteristic vector of the road-traffic environment and vehicle speed is discussed and modeled based on the GA-BP algorithm. Machine learning algorithms have undoubtedly been gaining more recognition in the field of vehicle speed prediction [4]. Among them, the BP neural network with its multi-layer feed-forward network trained by the error back propagation algorithm demonstrates the advantages of strong self-learning, self-adaptation, and fault tolerance [5]. However, for the traditional BP neural network, random selection of initial and threshold values leads the BP neural network to fall to the local minimum value, resulting in a slow convergence speed, fall into the local optimal value, and lack of global search ability. Therefore, the global optimization method of a genetic algorithm (GA) is adopted to determine the initial weight

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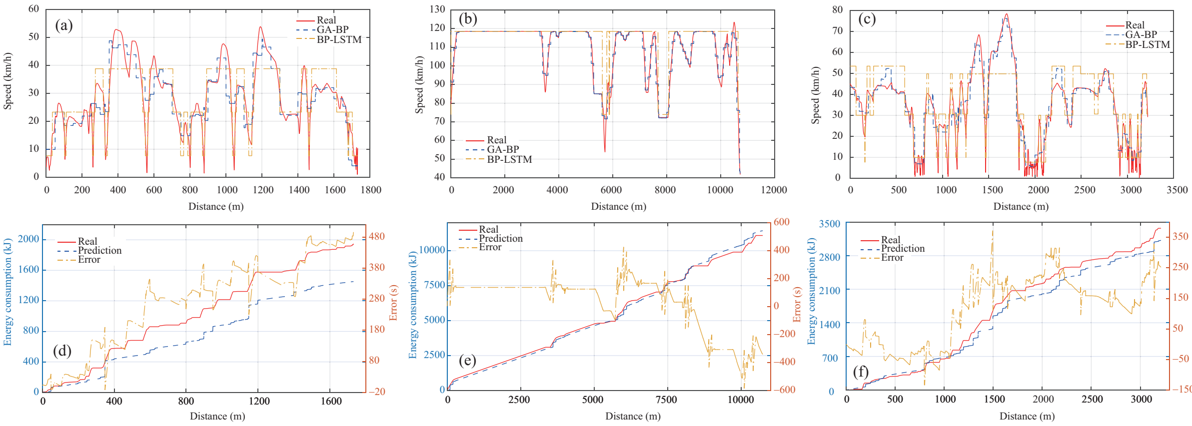

Figure 1 (Color online) The results of vehicle speed prediction and energy consumption on the new driving path. (a) and (d) urban; (b) and (e) expressway; (c) and (f) suburban.

and threshold of the BP neural network, so that its calculation error is close to the global minimum within the maximum range. Thus, falling into the local minimum is avoided, improving the convergence rate.

The main steps of the GA-BP algorithms are as follows: (a) initialization of population; (b) fitness function; (c) selection; (d) crossover; and (e) mutation.

Finally, the optimal individual value obtained using the GA replaces the initial value with the new weight and threshold of the network used to train the BP neural network for the optimal speed prediction results.

Evaluation index. To evaluate the accuracy of the speed prediction in the different sections of the newly planned driving path, the mean absolute error (MAE) and root mean square error (RMSE) are introduced as evaluation indexes.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|e_i| = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}{e_i}^2} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \tag{2}$$

where y_i is the true value, $\hat{y}_i$ is the predictive value, and n is the number of predictive values.

Comparative analysis. The data used in this study are derived from a planned driving path in the Nanjing city, tested by the research group. The model inputs include distance, speed limit, $\bar{v}$, number of lanes, cross, and traffic signal, and the output is v. In this algorithm, the parameters are set as follows: number of hidden layers $n_1 = 3$, number of nodes $n_2 = 30$, number of iterations $n_3 = 10$, population size $n_4 = 40$, crossover probability $p_1 = 0.4$, and mutation probability $p_2 = 0.02$.

Three types of roads, namely urban, suburban, and expressway, are selected for the prediction research. Along the historical driving path, the MAE and RMSE values for the urban roads are 3.3141 and 4.7645, respectively; those for suburban roads are 3.6154 and 5.3219, respectively; and the ones for expressway roads are 1.0536 and 2.2399, respectively. On the new driving path, the MAE value for urban roads is 4.4458 and the RMSE value is 6.3006, the MAE value for suburban roads is 4.1060 and the RMSE value is 5.9406, and the MAE value for expressway roads is 1.5261 with an RMSE value of 4.1766. The prediction accuracy of the GA-BP model on the new driving path is similar to that on the historical driving path, indicating that the model has a high level of robustness and accuracy in predicting different paths. This can be further illustrated by comparison with the BP-LSTM model completed by our team [6], as shown in Figure 1(a)–(c). It can be seen that the prediction tracking performance is significantly better than that of the BP-LSTM model.

Application in driving energy prediction. As mentioned above, energy consumption prediction represents a basic application of vehicle speed predictions. The calculation principle for the energy consumption prediction is shown using

$$P_e = \frac{1}{\eta}\left(\frac{Gfu}{3600} + \frac{Giu}{3600} + \frac{C_D A u^3}{76140} + \frac{\delta m u}{3600}\frac{\mathrm{d}u}{\mathrm{d}t}\right), \tag{3}$$

$$E = \sum_{t=1}^{n} P_e t, \tag{4}$$

where $m = 1580$ kg, $C_D = 0.3$, $\eta = 80\%$, $f = 0.015$, $C_D = 0.3$, $A = 1.8$ m^2, $\delta = 1.1$.

The dynamic tracking performance of the speed prediction has a great influence on the accuracy of the energy prediction, which is well reflected in

Figure 1(d)–(f). The prediction results for vehicle driving energy consumption are as follows: on the historical driving path, the prediction accuracy for the urban roads is 95.53%, for the suburban roads it is 90.68%, and for the expressway roads it is 92.76%. On the new driving path, the prediction accuracy for the urban roads is 74.56%, for the suburban roads it is 92.52%, and for the expressway roads it is 96.92%. Therefore, the vehicle speed prediction results of the long-term vehicle speed prediction model that uses the GA-BP algorithms based on the characteristic vector of road-traffic environment can be effectively applied for predicting vehicle energy consumption.

Conclusion. By combining the driver, vehicle, and traffic big data and real-time data, the road-traffic environment characteristic parameters were quantitatively described, and the sets of training and verification data points were constructed. Comparing the error characteristics of the long-term vehicle speed prediction models based on the BP-LSTM and GA-BP algorithms, the GA-BP algorithms were selected to establish a long-term vehicle speed prediction model. The accuracy of the vehicle speed prediction on a historical road path and new driving path was compared. The results show that the GA-BP speed prediction model based on the road-traffic environment characterization parameter description has better accuracy and better dynamic tracking characteristics than the previous models. Finally, the effectiveness of the proposed model for use in an energy consumption prediction scenario was verified.

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