Machine Learning Techniques for Protecting Intelligent Vehicles in Intelligent Transport Systems

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***Abstract*—Intelligent transport system (ITS) is the development direction of future transport systems, in which intelligent vehicles are the key components. In order to protect the safety of intelligent vehicles, machine learning techniques are widely used in ITS. For intelligent protection in ITS, the study introduces an improved driving behaviour modelling method based on Bagging Gaussian Process Regression. Meanwhile, to further promote the accuracy of driving behaviour modelling and prediction, Convolutional Neural Network-Long and Short-term Memory Network-Gaussian Process Regression are used for effective feature extraction. The results show that in the straight overtaking scenario, the mean absolute error, root mean square error and maximum absolute error of the improved Bagging Gaussian process regression method are 0.5241, 0.9547 and 10.7705, respectively. In the corner obstacle avoidance scenario, the improved Bagging Gaussian process regression method is only 0.6527, 0.9436 and 14.7531. Besides, the mean absolute error of the Convolutional Neural Network-Long and Short-term Memory Network-Gaussian process regression algorithm is only 0.0387 in the case of the input temporal image frame number of 5. This denoted that the method put forward in the study can provide a more accurate and robust modeling and prediction of driving behaviours in complex traffic environments, and it has a high application potential in the field of safety and protection of intelligent vehicles.**

Keywords*—*Intelligent vehicle protection; machine learning techniques; Gaussian Process Regression; convolutional neural networks; long and short-term memory networks

I. Introduction

With the rapid development of science and technology, intelligent transport systems have become a hot topic in today's society. In the intelligent transport system, intelligent vehicles play a crucial role [1]. However, with the popularity of intelligent vehicles, their safety problems are becoming more and more prominent. Driving behaviour modelling methods can help intelligent vehicles achieve safer and more efficient driving by predicting and simulating vehicle and driver behaviours. Traditional driving behaviour modelling methods include rule-based methods, probabilistic model-based methods, and so on. However, rule-based methods are difficult to adapt to the complex and changing traffic environment, and the formulation of rules often requires a lot of manual intervention and lacks adaptivity. Meanwhile, probabilistic model-based methods need to learn from a large amount of historical data, and model building requires high computational resources and time costs [2, 3]. Aiming at such problems, the study will explore the machine learning techniques for protecting intelligent vehicles in ITS, and introduce an improved driving behaviour modelling method based on Bagging Gaussian Process Regression (Bagging GPR), in order to achieve more accurate driving behaviour modelling and prediction In order to achieve more accurate modelling and prediction of driving behaviour, Convolutional Neural Network-Long Short-Term Memory-Gaussian Process Regression (CNN-LSTM-GPR) is used for effective feature extraction, to achieve good results in the field of intelligent vehicle security protection field to achieve good results. The study is composed of six main sections. The introduction is given in Section I. Section II gives details about the previous research work. Section III introduces the advanced driving behaviour modelling methods, the improved Bagging GPR driving behaviour modelling method is introduced in the first section, and the CNN-LSTM-GPR-based feature extraction method is presented in the second section. Section IV focuses on the experimental validation of the studied proposed method. Section V and Section VI summarize and discuss the experimental results and propose future directions. The contribution of the research is the introduction of advanced driving behaviour modelling methods, which help to improve the accuracy of driving behaviour modelling and prediction. These methods have important application value in the safety protection of intelligent vehicles and can effectively protect the safe driving of intelligent vehicles.

II. Literature Review

GPR is a nonparametric model for regression analysis of data with a Gaussian process prior, which is widely used. Deringer V L et al. put forward the GPR machine learning method to investigate the nature of atoms in chemistry and materials science. The method constructs an interatomic potential or force field using a Gaussian approximation of the potential framework and can be fitted with arbitrary scalars, vectors and tensors. The outcomes denoted that the method can effectively and accurately predict atomic properties [4]. Liu and other scholars developed two related data-driven models for the prediction of the effective capacity of lithium-ion batteries with a systematic understanding of the covariance function in GPR. The results illustrated that the raised models can accurately predict the battery capacity under different cycling modes [5]. Band et al. In order to accurately predict the groundwater level in arid areas, the researchers proposed to use the Support Vector Regression, GPR and its combination with Wavelet Transform for the prediction. The results show that the wavelet transform method combined with GPR has a strong performance advantage in GWL prediction compared to GPR [6]. Hewing L et al. researchers raised a model prediction control method with GPR for modelling and control of nonlinear dynamical systems. The method integrates the nominal system with the additional nonlinear part of the dynamics modelled as GPR. The findings indicated that the method can effectively assess the residual uncertainty [7]. Zhang Y's team developed a GPR-based predictive model for the optimisation of the magneto-thermal effect and relative cooling power of ferromagnetic lanthanum manganites. The model mainly searches for the correlation between RCP and lattice parameters by statistical learning. The findings denoted that the GPR model can predict RCP values efficiently and cost-effectively [8].

Driver behaviour recognition can detect and correct driver violations in time, reduce the accident rate and play an important role in vehicle protection. Xing and other scholars proposed a deep convolutional neural network-based driver activity recognition system for driver behaviour recognition and safe driving. The system utilizes a Gaussian mixture model to segment the original image to extract the driver's body from the background. The outcomes denoted that the raised system can accurately recognize seven driver activities with an average accuracy of 81.6% [9]. McDonald et al. found that an advanced driver assistance system needs to have a proper understanding of the driver's state, and therefore proposed a method for inference of self-vehicle driver's intention. The results show that the interaction between these modules has a significant impact on the lane change intention inference system [10]. Kabzan et al. researchers put forward a learning-based method to the problem of self-driving racing car control. The method was improved using a simple nominal vehicle model and GPR was used to account for model uncertainty. Test results show that on a full-size AMZ driverless race car, the method can improve the model and cut down the lap time by 10% [11]. Researchers such as Mozaffari have proposed a deep learning-based method for the problem of behavioural prediction of autonomous vehicles, which predicts the future state of a nearby vehicle by observing the surrounding environment. This approach provides better performance in more complex environments than traditional methods [12]. Hoel C J's team introduced a generalised framework that combines planning and learning in order to better address the tactical decision-making challenges of autonomous driving. The approach, based on the AlphaGo Zero algorithm and extended to continuous state spaces, shows better performance than the baseline approach [13].

In summary, numerous researchers and scholars have carried out extensive studies on GPR methods as well as driver behaviour recognition methods, but few scholars have applied improved GPR methods to driver behaviour recognition. Therefore, the study introduces the advanced GPR method for driver behaviour modelling, which is utilised with a view to achieving intelligent vehicle prediction and avoiding potential hazards.

III. Results

To protect the safety of intelligent vehicles, the study proposes an improved Bagging GPR driving behaviour modelling method, which uses GPR to design the base regressor and Bagging method to improve the whole effectiveness of the algorithm, as well as self-sampling method for the generation of new datasets. In order to achieve more accurate driving behaviour modelling and prediction, the study adopts CNN-LSTM-GPR for effective feature extraction, which mainly uses CNN to extract features from the input time-series image data, and inputs the extracted features into LSTM for processing Finally, the processed features are used as inputs for model fitting and prediction using GPR.

A. *GPR-Based Modelling of Intelligent Vehicle Driving Behaviour*

In intelligent transportation systems, to deal with different complex driving environments and promote adaptability and safety, driving behaviour modelling techniques play a key role. Based on this, the study introduces the GPR algorithm, which is a non-parametric Bayesian learning method that can be used for regression problems and is suitable for dealing with problems with uncertainty [14, 15]. In driving behaviour modelling, the perceived state quantities usually include the vehicle's attitude, speed, acceleration and other sensor data, and the GPR algorithm can be used to learn these perceived state quantities to build a model of the driving behaviour and perform real-time prediction and control. Therefore, the GPR algorithm is an effective method for modelling driving behaviour based on perceptual state quantities. However, the basic GPR algorithm has the issue of imitating a large amount of data and uneven distribution, to improve the algorithm's effectiveness, the study further proposes an improved Bagging GPR approach for driving behaviour modelling. The method firstly uses GPR to design the base regressor, and then uses the Bagging method to further improve the algorithm's whole effectiveness. The main process is to first randomly sample the driving behaviour in the training set by self-sampling method with playback, then train N GPR base learners using GPR, and lastly integrate the outputs of each base learner by averaging method to obtain the predicted values [16]. The driving behaviour modelling framework based on Bagging GPR is shown in Fig. 1.

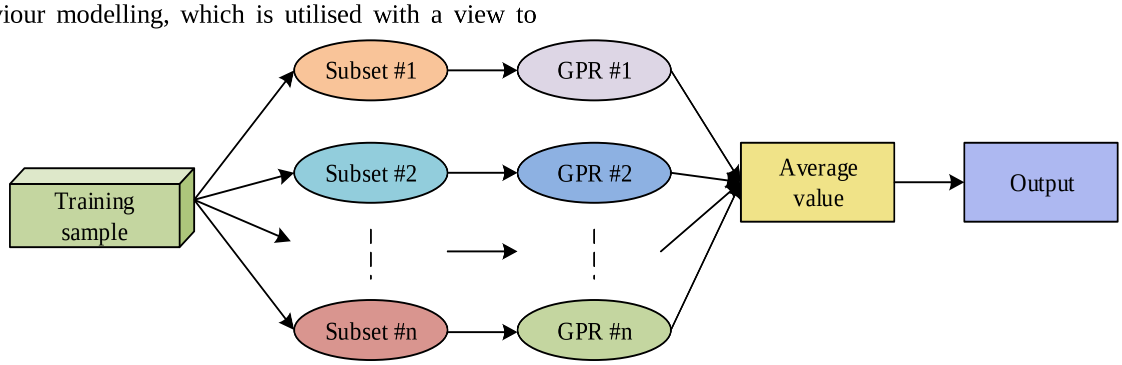


Fig. 1. A driving behaviour modeling framework based on Bagging GPR.

In the Bagging GPR-based driving behaviour modelling method, the self-sampling method is a method to generate a new dataset from an initial dataset. The specific steps of the method are, firstly, given a dataset containing m samples. Then, m random sampling operations are performed. In each sampling, a sample is randomly selected and placed into the new dataset, which is then placed back into the initial dataset. According to the limiting formula for probability estimation of the self-sampling method, it can be deduced that about 36.82% of the samples in the initial dataset never appeared in the new dataset, while about 63.2% of the samples appeared in the new dataset, which is calculated as shown in Eq. (1).

$$\lim_{m\to\infty}(1-\frac{1}{m})^m=\frac{1}{e} \tag{1}$$

A Gaussian process is a set of random variables, where any finite amount of random variables satisfy the joint Gaussian distribution.GPR mainly uses kernel methods for nonlinear mapping, and is a nonparametric model with good generalisation performance and global mapping ability. Given a training sample set D, where each element is a binary group containing an input vector s_i and an output vector a_i. The GPR model's output is worked out as shown in Eq. (2).

$$a=f(s)+\varepsilon \tag{2}$$

In Eq. (2), ε denotes the error, which satisfies the Gaussian distribution, and its representation is shown in Eq. (3).

$$\varepsilon \sim N(0,\delta_n^2) \tag{3}$$

In Eq. (3), δ_n^2 denotes the variance of the output error. a The prior distribution of is indicated as expressed in Eq. (4).

$$a \sim N(0,\delta_n^2+K) \tag{4}$$

In Eq. (4), K represents the covariance matrix. Based on the prediction samples as well as the training samples a joint Gaussian prior distribution can be obtained, which is represented as shown in Eq. (5).

$$\begin{bmatrix} a \\ a* \end{bmatrix} \sim N\left(0,\begin{bmatrix} K(s,s)+\delta_n^2 & K(s,s*) \\ K(s,s*)^T & K(s*,s*) \end{bmatrix}\right) \tag{5}$$

In Eq. (5), $s*$ and $a*$ denote the input vector and output vector of prediction, respectively. $K(s,s*)$ denotes the prediction and the training samples' the covariance matrix, and $K(s*,s*)$ denotes the prediction sample's self-covariance matrix. With the kernel function, the construction of the covariance matrix is mainly carried out. The kernel function chosen for the study is the radial basis function kernel, which is represented as shown in Eq. (6).

$$K(s,s*)=\alpha^2\exp(-\frac{(s-s*)^2}{2l^2}) \tag{6}$$

In Eq. (6), l is the kernel width of the radial basis function kernel, and α represents the hyperparameters, and the optimal hyperparameters are mainly obtained by the great likelihood method. After obtaining the optimal α, the the predicted value $a*$'s posteriori probability will be got based on the new $s*$, which is calculated as shown in Eq. (7).

$$p(a*|a)=\frac{p(a,a*)}{p(a)} \tag{7}$$

In Eq. (8), $a*$'s distribution is calculated.

$$a* \sim N(\hat{y}(s*),\hat{\delta}(s*)) \tag{8}$$

In Eq. (8), $\hat{y}(s*)$ represents the mean value, which is calculated as denoted in Eq. (9).

$$\hat{y}(s*)=K^T(s*)\cdot(K+\delta_n^2)^{-1}\cdot a \tag{9}$$

$\hat{\delta}(s*)$ denotes the variance, which is calculated as shown in Eq. (10).

$$\hat{\delta}(s*)=K(s*,s*)-K^T(s*)\cdot(K+\delta_n^2)^{-1}\cdot K(s*) \tag{10}$$

The steps of GPR application are shown in Fig. 2.

Aiming at the characteristics of large volume and uneven distribution of driving behaviour data, the study adopts the Bagging algorithm to promote of GPR algorithm's effectiveness. Bagging is an integrated learning method used to improve the accuracy of learning algorithms, and integrating and combining it can cut down the variance of the output, and promote the accuracy and stability of the algorithm. The Bagging method contains three parts, namely, sampling, training the base learner, and combining the output of three parts, and averaging method is used to obtain the output of the strong regressor, which is calculated as expressed in Eq. (11).

$$\hat{y}(s)=\frac{1}{N}\sum_{k=1}^{N}GPR_k(s) \tag{11}$$

The study proposes a Bagging GPR driving behaviour modelling method with improved sampling, due to the Bagging GPR algorithm's insensitivity to samples with large learning errors. The method raises the comprehensive effectiveness of the integrated regressor by increasing the sampling probability of samples, increasing the fluctuation of training samples, and increasing the attention of the base learner to samples with large training errors, which further reduces the maximum prediction error of the proposed algorithm [17]. The flow of the improved Bagging GPR approach for driving behaviour modelling is shown in Fig. 3.

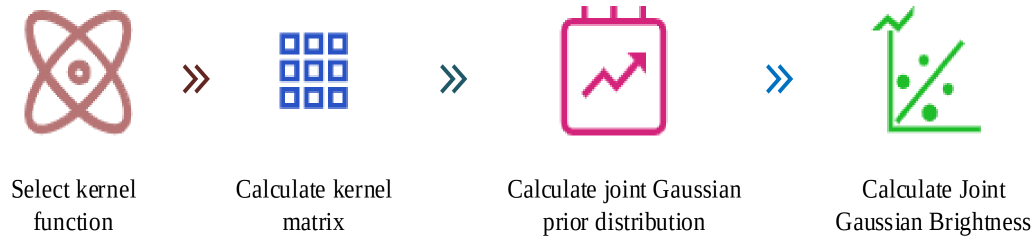


Fig. 2. Application steps of the GPR.

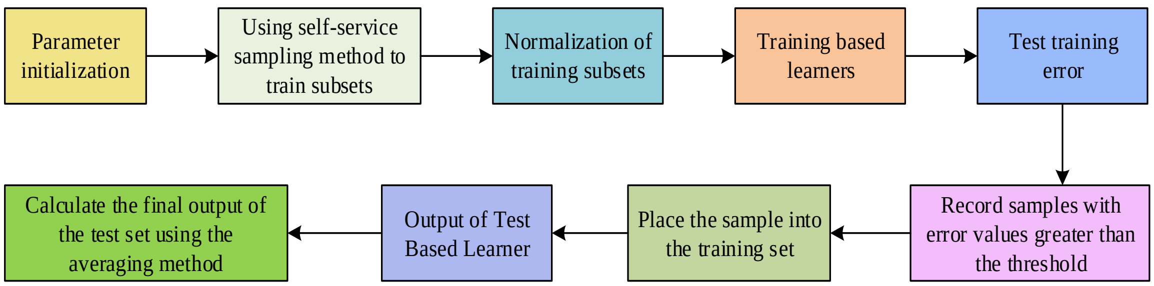


Fig. 3. Flow chart of improved Bagging GPR driving behaviour modelling method.

B. Intelligent Vehicle Feature Extraction Based on CNN-LSTM-GPR

To achieve driving behaviour modelling and prediction, effective feature extraction is required as input. Considering the characteristics of human drivers, driving behaviour learning should focus on the correlation between before and after states and actions. The study focuses on CNN-LSTM for time-series image feature extraction and fusion. Among them, CNN is a dedicated algorithm for image processing. CNN is not only able to efficiently downsize a large amount of image data into a small amount of feature data, but is also able to effectively extract the features related to a specific task through training. Convolutional, pooling, and fully connected layers are composed of CNN networks [18]. The output of the l convolutional layer is calculated as shown in Eq. (12).

$$C^l = \sigma(z^l) \tag{12}$$

In Eq. (12), σ represents the activation function, and z^l denotes the variables of the activation function of the l layer. The output of the pooling layer at l is calculated as shown in Eq. (13).

$$D^l = pool(C^l) \tag{13}$$

The output of the fully connected layer is calculated as shown in Eq. (14).

$$F^n = \sigma(F^{n-1} * W^n + b^n) \tag{14}$$

In Eq. (14), F^{n-1}, W^n, and b^n denote the output, weight matrix, and bias of the n th fully connected layer, respectively. The LSTM network is mainly applied to deal with the temporal prediction problem, whose input is the features extracted by the CNN at the time t, and the output is the predicted output at the time t. The dimensionality of the output is mainly related to the amount of output nodes of the LSTM network. The LSTM model can be viewed as a stack of cell units, each of which controls the transfer of information through a specially designed "gate" structure. The output of each cell consists of state and implicit layers, while the output of each implicit layer is jointly determined by three gates, including the inputting gate, forgetting gate and outputting gate. Each Cell unit selectively remembers and forgets the information through these three gates, and then passes it to the next Cell unit [19]. The LSTM network's structure is shown in Fig. 4.

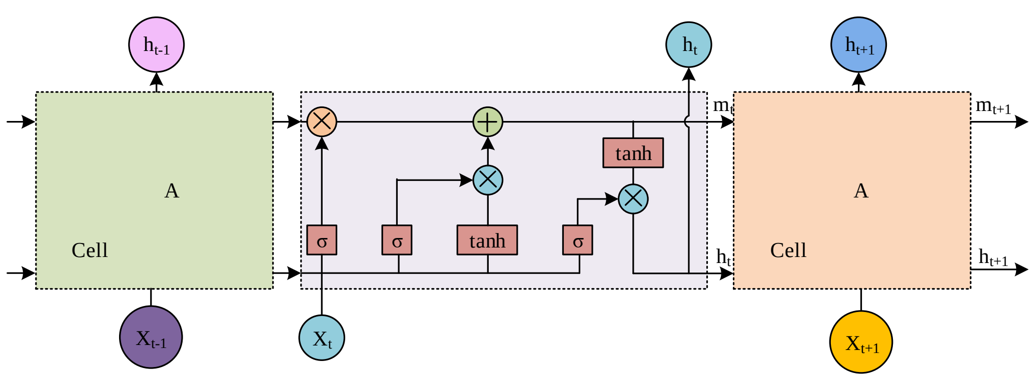


Fig. 4. Structure diagram of LSTM.

The CNN-LSTM's error loss function is mainly used to measure the degree of deviation between the labels and the output of the network. This loss function defines a criterion for evaluating the performance of the network and aims to cut down the difference between the actual and the desired output. During the training, the optimisation algorithm continuously adjusts the network parameters to minimise the loss function, thus making the network's prediction more accurate. Its calculation is shown in Eq. (15).

$$E = \frac{1}{N}\sum_{i=1}^{N}\|y_i - a_i\|_2^2 \tag{15}$$

In Eq. (15), y_i represents the CNN-LSTM network's output, a_i represents the labels of the expert demonstration teaching, and N is the size of the Batch size. The CNN-LSTM method considers the temporal correlation between image sequences while considering the image feature extraction. This method can promote the simulation accuracy of driver behaviour. The neural network's layer is a combination of convolutional and pooling layers. The specific configuration of the convolutional layers is as follows: the first, second, third, fourth, and fifth convolutional layers have a convolutional kernel size of 5 × 5, 5 × 5, 5 × 5, 3 × 3, and 3 × 3, respectively, and a feature map number of 24, 36, 48, 64 and 64, respectively. The first, second, fourth, and fifth convolutional layers have a pooling downsampling window size of 2 × 2 steps with a step size of 2, while the third layer has a pooling downsampling window size of 1 × 2 steps with a step size of 2. Subsequently these feature maps are fed into the fully-connected layer, which has a node count of 512. The fully connected layer is followed by two LSTM layers. Finally, the output of the LSTM layer is connected to the output layer, which outputs the normalized value of the steering wheel angle [20]. A schematic diagram of the CNN-LSTM feature extraction network structure is shown in Fig. 5.

The research focuses on combining CNN-LSTM with GPR to enhance the understanding of the mapping relationship between temporal features and driving behaviour. The core idea of the method is to utilize GPR to further optimize the features of the CNN-LSTM to promote the fully connected layer's structure. The CNN-LSTM accumulates errors layer-by-layer during the training process, which limits its generalisation ability. Since the fully connected layer is similar to that of CNN, its generalisation ability is limited. By using the GPR method, the perfect temporal feature extraction effect of CNN-LSTM is fully utilized, while the fitting mapping ability between temporal features and driving behaviour is further improved by GPR, to improve the comprehensive performance of the algorithm. The detailed process of the CNN-LSTM-GPR method is denoted in Fig. 6.

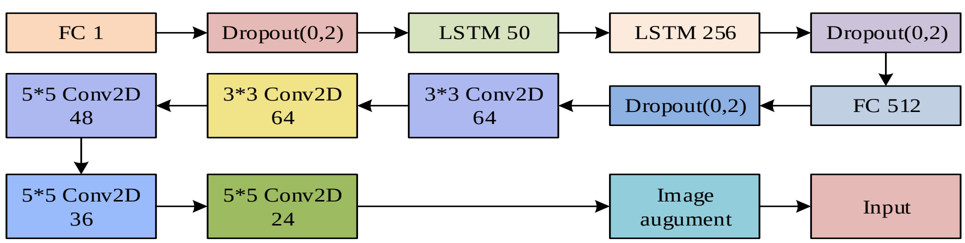


Fig. 5. Schematic diagram of CNN-LSTM feature extraction network structure.

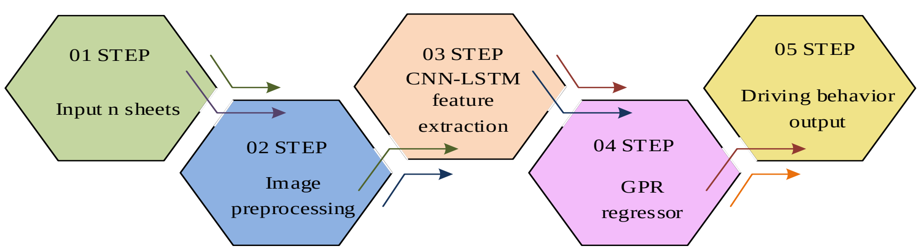


Fig. 6. The process of CNN-LSTM-GPR method.

IV. Intelligent Vehicle Protection Analysis based on GPR Methodology

This chapter focuses on the experimental analysis of the improved Bagging GPR and the CNN-LSTM-GPR methods proposed by the study. Among them, for the improved Bagging GPR method, the study analyses the effect of driving behaviour modelling and verifies the performance from two scenarios, namely the straight overtaking scenario and the corner obstacle avoidance scenario. The study verifies the effectiveness of each algorithm from different input image frames, and compares the steering wheel corner prediction results of different algorithms to evidence the performance of the raised method.

A. Driving Behaviour Modelling Analysis Based on Improved Bagging GPR Methodology

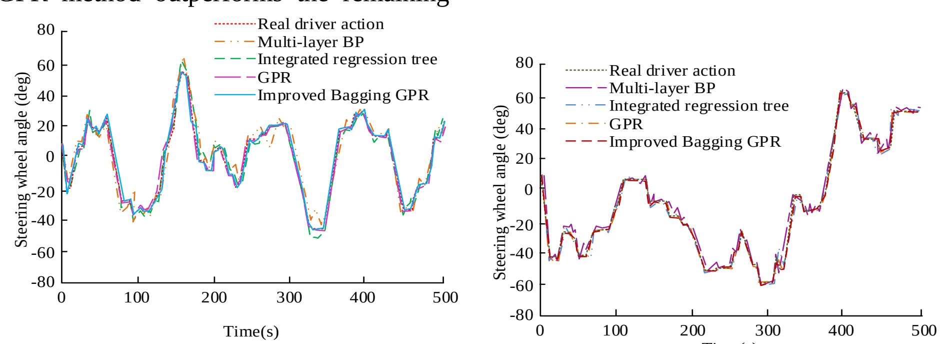
To verify the effectiveness of the improved Bagging GPR method, firstly, the driving behaviours of the straight overtaking scenario as well as the corner obstacle avoidance scenario are modelled and learned. At the same time, three driver behaviour modelling methods, namely, multi-layer Back Propagation Algorithm (BP), Integrated Regression Tree and GPR, are selected for performance comparison with them. The parameter settings of each method are expressed in Table I.

TABLE I. PARAMETER SETTINGS FOR EACH METHOD

Method	Project	Parameter
Multi-layer BP network	Number of nodes of the two hidden layers	75, 15
Integrated regression tree	Integrated learning cycle	100
	Learner	Regression tree
GPR	Kernel function	Gaussian kernel function
	Nuclear width	1
	Noise parameters	0.1
Improved Bagging GPR	Number of iterations of the Bagging	20
	The size of the Bagging	2000
	Error threshold	3

The steering wheel angle prediction results of different driving modelling methods for different scenarios are indicated in Fig. 7. From Fig. 7, in contrast with the remaining three modelling methods, the driving behaviour modelling method of the improved Bagging GPR has a better fitting performance with the actual steering wheel angle and a higher matching accuracy. Whereas, the multi-layer BP algorithm has the largest deviation from the actual steering wheel angle, representing its worst modelling performance. It indicates that the proposed algorithms in the study have high prediction accuracies in modelling driving behaviours in both straight overtaking scenarios as well as cornering obstacle avoidance scenarios.

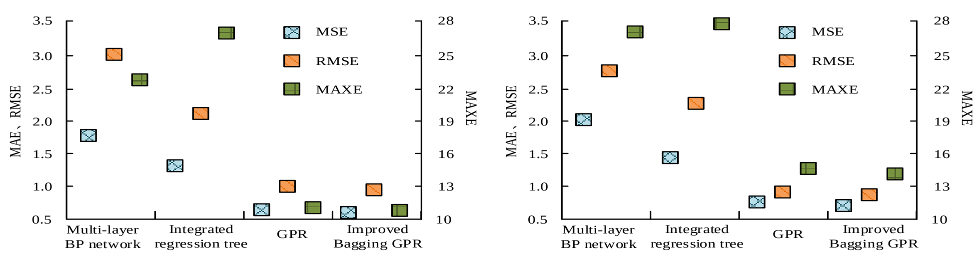
The experiments continue to use Mean Square Error (MSE), Root Mean Square Error (RMSE) and Maximum Absolute Error (MAXE) to experimentally validate the different driving behaviour modelling methods. The comparative results of the steering wheel corner prediction performance of each method in different scenarios are expressed in Fig. 8. From Fig. 8, the improved Bagging GPR method outperforms the remaining three methods for steering wheel angle prediction in the straight overtaking scenario as well as in the corner obstacle avoidance scenario. Among them, in the straight overtaking scenario, the MAE, RMSE, and MAXE of the improved Bagging GPR method are 0.5241, 0.9547, and 10.7705, respectively, whereas those of the multilayer BP algorithm are as high as 1.7763, 3.0334, and 23.0549, respectively. The integrated regression tree is as high as 1.2863, 2.1538, 27.349, and 1.2863, respectively, 2.1538, and 27.3626, respectively. The indexes of GPR are 0.5569, 0.9638, and 10.9934, respectively, which are improved by 0.0328, 0.0091, and 0.2184 compared with the improved Bagging GPR method. At the same time, in the corner obstacle avoidance scenario, the MAE, RMSE, and MAXE of the improved Bagging GPR method are 0.660, 0.660, and 0.660, respectively. MAE, RMSE, and MAXE are 0.6527, 0.9436, and 14.7531, respectively, which are 1.383, 1.8274, and 12.8996 less than the multi-layer BP algorithm, suggesting that the improved Bagging GPR method has better performance and stability when dealing with complex driving behaviour modelling problems.



(a) Comparison of predicted steering wheel angles in straight overtaking scenarios

(b) Comparison of predicted steering wheel angles in obstacle avoidance scenarios on curves

Fig. 7. Prediction results of steering wheel angles in different scenarios.



(a) The results of various indicators in the scenario of overtaking on the straight track

(b) The results of various indicators in the obstacle avoidance scene of bends

Fig. 8. Comparison of steering wheel angle prediction performance of various methods in different scenarios.

B. Feature Extraction Analysis Based on CNN-LSTM-GPR Algorithm

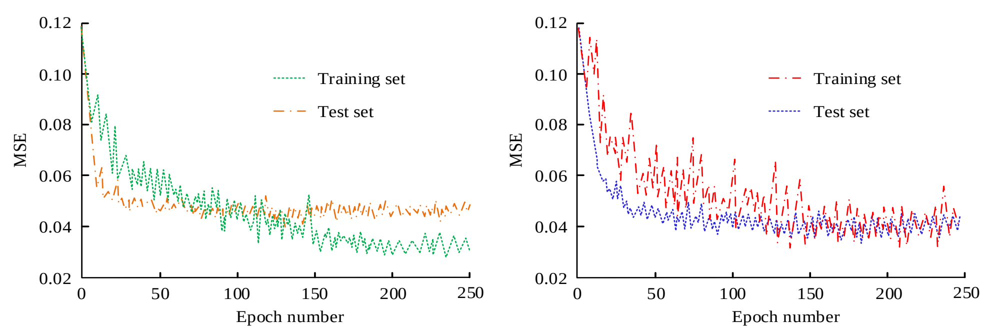
The study first uses a CNN-LSTM network to extract the features of various input sequence images. In terms of training parameter settings, the specific settings are denoted in Table II.

The experiments have been conducted on Apollo dataset using CNN-LSTM network with an input image sequence of 3 and an input image sequence of 5. The variation of the training error loss function is denoted in Fig. 9. The MSE of the training and test set for the case of the input image sequence of 3 is lower than the case of the input image sequence of 5. In particular, the MSE of the test set with an input image sequence of 3 converges to 0.0415 at about 25 iterations, which is 0.014 higher than the case with an input image sequence of 5. This indicates that, for the task of learning driving behaviours, the use of the CNN-LSTM network with longer input image sequences can extract the image features in a better way and help to improve the model's accuracy and generalization ability.

The experiments continued with GPR to fit the features for mapping driving behaviour. The CNN-LSTM-GPR algorithm's parameters were set as below: the kernel function was RBF, the kernel width parameter was 0.5, and the noise parameter was 0.3. The experiments were conducted using 50-dimensional features extracted by the CNN-LSTM on the Apollo dataset for driving behaviour Learning. To ensure the accuracy of the experiments, the study conducted a total of 10 experiments and took the effective average as the final experimental results. Meanwhile, MSE is chosen as the evaluation index of the experiment. The test outcomes of various driving behaviour learning methods under different input timing image frame numbers are shown in Fig. 10. The CNN-LSTM-GPR algorithm can obtain lower MSE under different input time-series image frame numbers, among which, under the input time-series image frame number of 3, the MSE of the CNN-LSTM-GPR algorithm is only 0.0405, which is 0.010 less than that of the CNN-LSTM algorithm under the input time-series image frame number of 5, the MSE of the CNN-LSTM-GPR algorithm is only 0.0405, which is 0.010 less than that of the CNN-LSTM algorithm. The MSE of the CNN-LSTM-GPR algorithm is 0.0387, which is reduced by 0.0023 in contrast with the CNN-LSTM algorithm. The MSE values of the individual algorithms for the input temporal image frame number of 5 are lower compared to the case where the input temporal image frame number is 3. It shows that the CNN-LSTM-GPR algorithm has higher accuracy in learning to mimic the driving behaviour of the temporal images and the performance of the algorithms is better at a higher number of input temporal image frames.

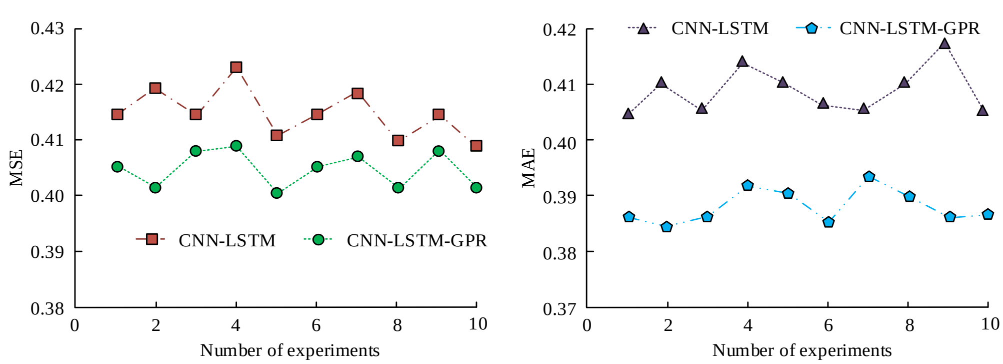
TABLE II. TRAINING PARAMETER SETTINGS

Project	Parameter
Learning rate	0.0001
Optimizer	Adam
Dropout	0.2
Batch size	20
Number of training samples	5000
Number of training rounds	200
Training time	9h



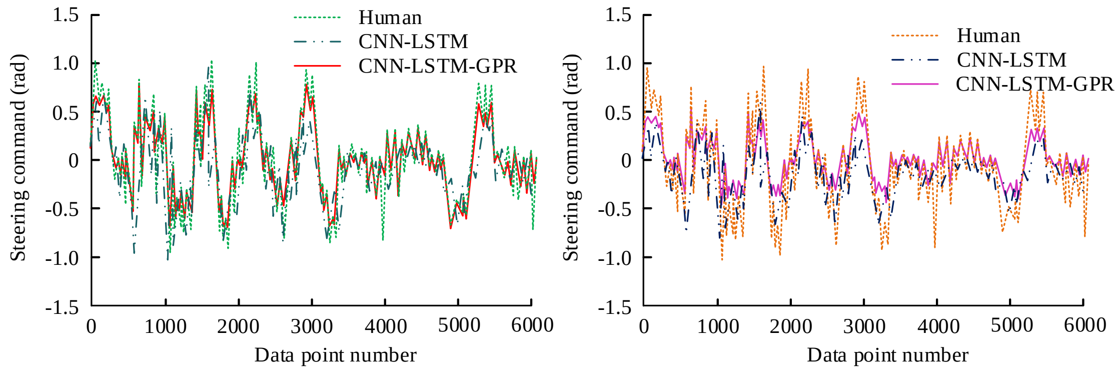
(a) Change in loss function of input timing image frame number 3 (b) Change in loss function of input timing image frame number 5

Fig. 9. Changes in training error loss function for different input image sequences.



(a) MSE value when the input timing image frame number is 3 (b) MSE value when the input timing image frame number is 5

Fig. 10. MSE values under different input timing image frames.



(a) Comparison of steering wheel angle prediction when the input image frame number is 3

(b) Comparison of steering wheel angle prediction when the input image frame number is 5

Fig. 11. Steering wheel angle prediction results of different driving behaviour learning methods based on time series information.

To evidence the function of the CNN-LSTM-GPR algorithm, the study further compares the steering wheel corner prediction outcomes of various driving behaviour learning methods with temporal information on the test set, and the research findings are indicated in Fig. 11. From Fig. 11, the CNN-LSTM-GPR based driving behaviour learning model can simulate human driving behaviour better compared to the CNN-LSTM model. It's learned driving actions are smoother, the coherence between actions is more solid, and the learning error is smaller, which outperforms the CNN-LSTM model. It can also be seen that when five consecutive frames of images are input, the driving behaviours simulated by the CNN-LSTM-GPR-based driving behaviour learning model fluctuate less and the movements are more coherent. This further confirms that introducing more temporal information helps to improve the performance of driving behaviour learning.

Further research was conducted to verify the computational efficiency of the CNN-LSTM-GPR algorithm, using CNN-LSTM algorithm, Extreme Gradient Boosting (XGBoost) algorithm, and Seasonal Autoregressive Integrated Moving Average (SARIMA) model for performance comparison. The calculation time for different algorithms in predicting driving behavior is shown in the table. According to the table, the computation time of the CNN-LSTM-GPR algorithm is only 0.5213 seconds, which is lower compared to the XGBoost and SARIMA algorithms. The computation time of the CNN-LSTM algorithm is slightly lower than that of the CNN-LSTM-GPR algorithm, because the algorithm integrates Gaussian Process Regression to handle uncertainty, thereby increasing computation time. However, overall, the CNN-LSTM-GPR algorithm has better predictive performance.

TABLE III. CALCULATION TIME FOR DIFFERENT ALGORITHMS

Algorithm	Runtime (s)
CNN-LSTM	0.4926
XGBoost	1.6397
SARIMA	15.3969
CNN-LSTM-GPR	0.5213

V. DISCUSSION

An improved Bagging GPR method has been proposed for intelligent protection in intelligent transportation systems. The results showed that in the scenario of overtaking on a straight line, the MAE, RMSE, and MAXE of the improved Bagging GPR method were 0.5241, 0.9547, and 10.7705, respectively. Meanwhile, in the scenario of obstacle avoidance on curves, the MAE, RMSE, and MAXE of the improved Bagging GPR method are 0.6527, 0.9436, and 14.7531, respectively. Compared to the multi-layer BP algorithm, its various indicators have decreased by 1.383, 1.8274, and 12.8996, respectively. ZHONG Q et al. proposed a tool wear prediction method based on maximum information coefficient and improved Bagging GPR. The results show that this method has significant advantages in predictive performance [21]. The Bagging GPR method demonstrates high prediction accuracy in all aspects. The reason is that the improved Bagging GPR method integrates multiple GPR models, each trained with a different subset of data, and then averages or weights their prediction results, thereby reducing the variance of the model. At the same time, this method increases the attention of the base learner to samples with large training errors, further reducing the maximum prediction error and improving the overall performance of the ensemble regressor.

In the effectiveness verification experiment of the CNN-LSTM-GPR algorithm, the driving behavior learning model based on CNN-LSTM-GPR can better simulate human driving behavior compared to the CNN-LSTM model. The driving actions it learns are smoother, with stronger coherence between actions and smaller learning errors, and its performance is better than that of the CNN-LSTM model. When five consecutive frames of images are input, the driving behavior learning model based on CNN-LSTM-GPR simulates less fluctuation and more coherent actions. Chen H and other researchers proposed a CNN-GPR method for driving behavior learning, which addresses the problems of low learning accuracy and poor generalization performance in traditional driving behavior learning methods. They also introduced LSTM and proposed a CNN-LSTM-GPR method for driving behavior learning using time-series images. The results show that the proposed CNN-LSTM-GPR method can fully utilize the temporal information of the image, resulting in smaller simulation errors [22]. Compared with the CNN-LSTM method, this method can further improve learning accuracy and exhibit better generalization performance. This is similar to the research findings. The reason is that the CNN-LSTM-GPR method can effectively utilize temporal image information. Temporal information includes the temporal sequence of consecutive frame images, which helps capture dynamic changes and coherence in driving behavior. By introducing the GPR (Gaussian Process Regression) model, it is possible to more accurately model the spatiotemporal dynamics of driving behavior, thereby making the learned driving actions smoother and more coherent.

VI. Conclusion

Intelligent vehicle safety protection in intelligent transport systems is of great significance. For intelligent protection in intelligent transportation systems, the study successively introduces an improved Bagging GPR=driving behaviour modelling method and a feature extraction method with CNN-LSTM-GPR algorithm. The findings denoted that compared with the remaining three modelling methods, the driving behaviour modelling method of the improved Bagging GPR has better fitting performance with the actual steering wheel angle and higher matching accuracy. Whereas, the multi-layer BP algorithm has the largest deviation from the actual steering wheel angle, which represents its worst modelling performance. Meanwhile, when the input image sequence of the CNN-LSTM network is 3, the MSE of the test set converges to 0.0415 at about 25 iterations, which is an improvement of 0.014 compared to the case when the input image sequence is 5. In addition, compared to the CNN-LSTM model, the driving behaviour learning model with CNN-LSTM-GPR can more accurately simulate human driving behaviour. Its learned driving actions are smoother, the articulation between actions is more natural, and its learning error is relatively smaller, so the whole effect is better than that of the CNN-LSTM model. In addition, when five consecutive frames of images are input, the driving behaviours simulated by the CNN-LSTM-GPR-based driving behaviour learning model show less fluctuation and more coherent movements. It shows that the improved Bagging GPR method and CNN-LSTM-GPR feature extraction method can provide more accurate and smooth driving behaviour modelling and learning schemes for intelligent vehicles in ITS. However, the drawback of this study is that it only focuses on specific scenarios and environments, which may limit the universality and scalability of the proposed technology in a wider range of driving conditions and challenges. Future research needs to expand its scope to cover more diverse scenarios, road conditions, and driving behaviours to ensure the effectiveness and robustness of the developed models in real-world applications.

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