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RESEARCH ARTICLE

The Prediction Model for Road Slope of Electric Vehicles Based on Stacking Framework of Deep Learning

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ABSTRACT Accurate real-time information on road slopes and the capacity to forecast future moment gradient values are critical for the vehicle control, stability, and driving comfort. Thus, this study proposes a stacking model method for road slope estimation of electric vehicles. Gated Circulation unit (GRU), Convolutional Neural Network (CNN), and CNN-GRU are used as the base classifiers, and Multilayer Perceptron (MLP) is used as a meta-classifier. The vehicle dynamics equations are examined to select the appropriate parameters to feed into the base classifier for training. The meta-classifier is trained using the estimated results from the basic classifier. The current slope values are estimated by slicing the training set by data sampling time and windowing the training data set to predict the future slope values in 2s, 3s, and 4s. Road experiments are conducted, and error indicators are selected for evaluation. The stacking model is compared with each base classifier, Adaptive Kalman filter, Recursive Least Squares with Forgetting Factor and Back Propagation Neural Network for estimating the current moment slope, and it is verified that the stacking model can better estimate the current slope value and outperform the conventional algorithm. Comparing the stacking model with the predicted results of each base classifier for future time slope prediction shows that the stacking model is more accurate at predicting the slope values in the short future time.

INDEX TERMS Electric vehicles, stacking model, gated circulation unit, convolutional neural networks, road slope prediction.

I. INTRODUCTION

Currently, the world is facing the challenges of environmental issues and energy crises [1]. Many countries are developing electric vehicles because of their low energy consumption and zero pollution [2], [3]. Road slope is an important parameter of the vehicle control system [4]. Accurate road slope information has a significant impact on enhancing the comfort, safety, and economy of electric vehicles [5], [6]. With the development of driverless and smart driving technologies, it is essential to optimize vehicle control techniques by efficiently forecasting future road slopes [7], [8].

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Numerous academics have studied the estimation of road slope, and the methods for road slope estimation are mainly divided into two major categories: One category of the estimation method is based on additional sensors to measure the road slope directly or indirectly by inclinometers [9], GIS [10] (Geographic Information System), GPS [11], [12], [13] (Global Positioning System), smart phone [14], accelerometers [15], etc. The other category is the method based on the dynamics model, in which the road slope is estimated by various algorithms based on dynamics model. The Kalman Filter (KF) and its variations [16], [17], [18], [19], as well as the Recursive Least Squares (RLS) method and its variations [20], [21], are frequently used; however, because the dynamics equation couples the mass and slope,

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and because a single algorithm has a poor decoupling performance, the present study focuses primarily on the joint estimation of the road slope and the entire vehicle mass by a variety of methods. Kim et al. used the Kalman filter to first estimate slope, velocity, and acceleration, and then the estimates were used as recursive least squares inputs to estimate the vehicle mass [22]; Sun et al. used an extended Kalman filter to estimate the vehicle mass and slope, and then used recursive least squares quadratic estimation to weigh the two estimates to obtain the optimal solution [23]; Chu et al. combined high-pass filters with recursive least squares to estimate the whole vehicle mass based on the accurate driving force of electric vehicles, and later estimated the road slope by combining kinematics and dynamics [24]; Chen et al. performed slope estimation based on the longitudinal motion characteristics of electric vehicles by fusing slope information from a 1st-order dilation observer with slope information separated from the acceleration sensor using a forgetting factor recursive squares method [25]. Li et al. considered the time-varying friction coefficient and systematic error using a double forgetting factor recursive least squares method to first estimate the whole vehicle mass and then the extended Kalman filter to estimate the road slope [26], Feng et al. proposed a multi-model multi-data fusion algorithm for slope estimation [27]. Jiang et al. proposed a two-stage adaptive road slope and overall vehicle mass estimation method considering multiple driving resistance factors [28]. With the development of machine learning, deep learning is widely used in various fields such as stock prediction [29], electricity consumption [30], wind power prediction [31], hybrid vehicle battery state estimation [32], etc. With the rapid development of machine learning, deep learning can be applied to the estimation of road slopes, Torabi et al. used feedforward neural networks for road slope estimation in heavy vehicles [33]; Wang et al. proposed an LSTM-based method for estimating the road slope of fuel cell vehicles [34].

In summary, in the method using additional sensors, the signal of GIS, GPS and smart phone can be disturbed or even no signal in the tunnel or forest, the estimation accuracy in the method using inclinometer, accelerometer depends on the sensor accuracy and installing high precision sensors in a vehicle might raise the cost of the vehicle. In the dynamics-based approach, a single algorithm is less effective in decoupling the dynamics equations, and the variation of the engine or drive motor torque during vehicle braking leads to poorer estimation results. The multi-model technique necessitates sophisticated decoupling calculations, and the estimation results are influenced by modeling accuracy and still contain large mistakes when the car is braked. The road slope value will change with time during the actual driving, so the road slope value can be regarded as a time-varying parameters. Deep learning methods has also yielded better results in time series prediction. Also, neural networks can take vehicle braking into account in model training to assure vehicle braking accuracy, and time series can obtain predictions for the future time, which traditional approaches cannot. The current research method is primarily used to investigate current moment slope estimation, with minimal research on future moment road slope prediction.

Based on the above analysis, this paper proposes a stacking model-based slope estimation method for electric vehicle roads, which uses Gated Circulation Unit (GRU), Convolutional Neural Network (CNN), and Gated Circulation Unit-Convolutional Neural Network (CNN-GRU) as base classifiers of the stacking model and uses MLP (Multilayer Perceptron) as a meta-classifier to train the estimation results of the three base classifiers to obtain the final slope estimation results. The vehicle driving process is analyzed, and appropriate parameters are selected as model inputs. According to the model characteristics, the input data can be divided into window forms of different lengths to estimate the current road slope and predict the road slope in a short period of time in the future. All model inputs are collected using the vehicle's CAN bus, eliminating the need for additional sensors. Model training is distinct from testing, and the test set can be completed quickly. To validate the algorithm's results, an electric vehicle is chosen for testing, and the integrated model's slope prediction is performed using actual CAN bus measurement data, with the slope prediction results compared to the base model prediction results.

II. PROPOSED METHOD

A. FEATURE SELECTION

Define The specific structure and complexity of the neural network model are determined by the input feature parameter selection [35]. Therefore, the electric vehicle dynamic model is analyzed, and the appropriate feature parameters are selected as inputs to the algorithm. Analyzing the vehicle dynamics theory during the vehicle driving process, the total traction force $F_{\mathrm{W}}(t)$ as

$$F_{\mathrm{W}}(t) = F_{\mathrm{aero}}(t) + F_{\mu}(t) + F_{\mathrm{grade}}(t) + F_{\mathrm{a}}(t) \tag{1}$$

where $F_{\mathrm{aero}}(t)$ is the air resistance, $F_{\mu}(t)$ is the rolling resistance, $F_{\mathrm{grade}}(t)$ is the ramp resistance, $F_{\mathrm{a}}(t)$ is the acceleration resistance.

The above equation expands to:

$$\frac{T(t)\mathrm{i}\eta}{\mathrm{r}} = \frac{\mathrm{C_D A}\rho v(t)^2}{2} + \mu \mathrm{mg}\cos\theta(t) + \mathrm{mg}\sin\theta(t) + \delta m a(t) \tag{2}$$

where $T(t)$ is the motor torque, i is the gear ratio of the main reducer in the drive axle of the vehicle, r is the rolling radius of the wheel, η is the mechanical efficiency of the transmission system, $\mathrm{C_D}$ is the air resistance coefficient, A is the windward area, ρ is air density, $v(t)$ is Vehicle speed, μ is the rolling resistance coefficient, m is Vehicle mass, g is the gravitational acceleration, $\theta(t)$ is road slope, δ is the conversion coefficient of vehicle rotating mass, $a(t)$ is Vehicle acceleration.

According to (2), the road slope $\theta(t)$ as can be written as

$$\theta(t) = f_1(F_{\mathrm{W}}(t), F_{\mathrm{aero}}(t), F_{\mathrm{a}}(t)) \tag{3}$$

During the electric vehicle driving process, the vehicle control module regulates the power battery output based on the accelerator pedal opening degree α_{acc}, and the output power drives the drive motor rotation through the inverter. Vehicle braking requires a braking signal α_{bra}. Electric vehicles generally use braking energy recovery. The vehicle brake motor in the transmission unit will convert energy through the inverter, BDU (Battery energy Distribution Unit) into electrical energy back to the battery, and then further into drive energy while providing braking torque so that the motor swiftly stops the pointless inertia spinning. From the above process, it can be obtained that the driving force is related to the drive motor torque, accelerator pedal opening and brake pedal. $F_W(t)$ can be written as

$$F_W(t) = f_2(T(t), \alpha_{acc}(t), \alpha_{bra}(t)) \tag{4}$$

In general, the vehicle mass, rolling resistance coefficient, air density, air resistance coefficient, windward area, and gravitational acceleration are basically constant during the driving processes, and they are regarded as constant. The motor torque, vehicle speed, vehicle acceleration, accelerator pedal opening degree, braking signal and road slope are time-varying parameters that change at any time. Considering that this paper is to analyze the vehicle driving state variables to select the appropriate characteristic variables, it does not involve the relationship between road slope and other quantitative. Thus, the (3) can be reduced to a functional representation of the time-varying parameters:

$$\theta(t) = f(v(t), a(t), T(t), \alpha_{acc}(t), \alpha_{bra}(t)) \tag{5}$$

The motor torque, vehicle speed, vehicle acceleration, accelerator pedal opening α_{acc}(t), and braking signal α_{bra}(t) were then selected as algorithm inputs, and these parameters are available from the vehicle CAN bus.

B. STACKING ENSEMBLE LEARNING

Stacking is also known as cascading generalization method [36]. A two-stage model is used in the stacking approach. The model in the first stage is a model with the original training set as input, called the base model, and several base models can be trained. The meta-model is the second stage of the model, which uses the predictions of the base model on the initial training set as the training set and the predictions of the base model on the initial test set as the test set. The training set for each base classifier is the complete original training set. After training each base classifier, all the outputs are combined as a new training set to train the second stage of the meta-classifier. The stacking model architecture is shown in Fig. 1.

In this paper, GRU [37], CNN [38], and CNN-GRU are selected as the base classifiers, and MLP is chosen as the meta classifier. GRU is a type of Recurrent Neural Network (RNN), which can solve the problems such as the inability of long-term memory and gradient in backpropagation in RNN, similar to Long-Short Term Memory (LSTM). Since LSTM has better time series prediction performance [39] and GRU has similar performance compared to LSTM. However, it is easier to compute [40], which largely improves the

Algorithm: Stacked Ensemble Network for Road Slope Prediction

Input: Training data $D = \{x_i, y_i\}_{1 \le i \le N}$, Test data D_{test}, Sub-models
Output: Result from the stacked ensemble network
Generate probability scores from predictions made by sub-models (S):
for $s = 1$ to S **do**
  Get predictions $P^{(s)}$ based on D^{train}
end for
$P^{(st)} = \text{Concatenation}([P^{(1)}, P^{(2)}, \ldots, P^{(S)}])$
Create a new dataset, D_{res} containing the probability scores and target labels:
for $i = 1$ to N **do**
  $D_{\text{res}} = \{P^{(st)}, y_i\}$
end for
Train a meta-learner, M_{meta} with the newly created dataset, D_{cv}
result = prediction M_{meta}
return result

training efficiency and reduces the arithmetic cost, Thus, GRU is chosen to predict the time-varying series of road slope. The GRU model used in this paper uses a 3-layer GRU unit overlay and outputs the results using a fully connected neural network. CNN is commonly used in the image field. However, its feature extraction ability can tap the intrinsic connection between data and reduce the size and complexity of the original data, so it also has good applications in sequence processing. 1-dimensional CNN typically utilizes one-dimensional convolutional kernels to process 1-dimensional data and can efficiently extract features from fixed-length segments throughout the dataset. 1-dimensional CNN can also be applied to time series prediction [41]. Empirically, if the variability between the base models to be combined is significant, then there is usually a better result afterward. Thus, 1-dimensional CNN is chosen as base classifier. The CNN model used in this paper uses three convolutional layers with three maximum pooling layers superimposed on each other and outputs the results through a fully connected neural network. CNN-GRU is also used for the estimation of time series [42]. In CNN-GRU, CNN extracts the effective features of the data, but the extracted features are more local in focus, and the dependencies of the local features in the time step can be better captured by feeding the extracted features through GRU. The CNN-GRU model utilized in this paper uses two convolutional layers two pooling layers, and three GRU layers, and the results are output through MLP.

III. EXPERIMENTS

A. EXPERIMENT EQUIPMENT

The experiment was conducted on a BAIC EX360 new energy vehicle, and Table 1 shows the basic parameters of the vehicle. The experiment equipment includes T-BOX,

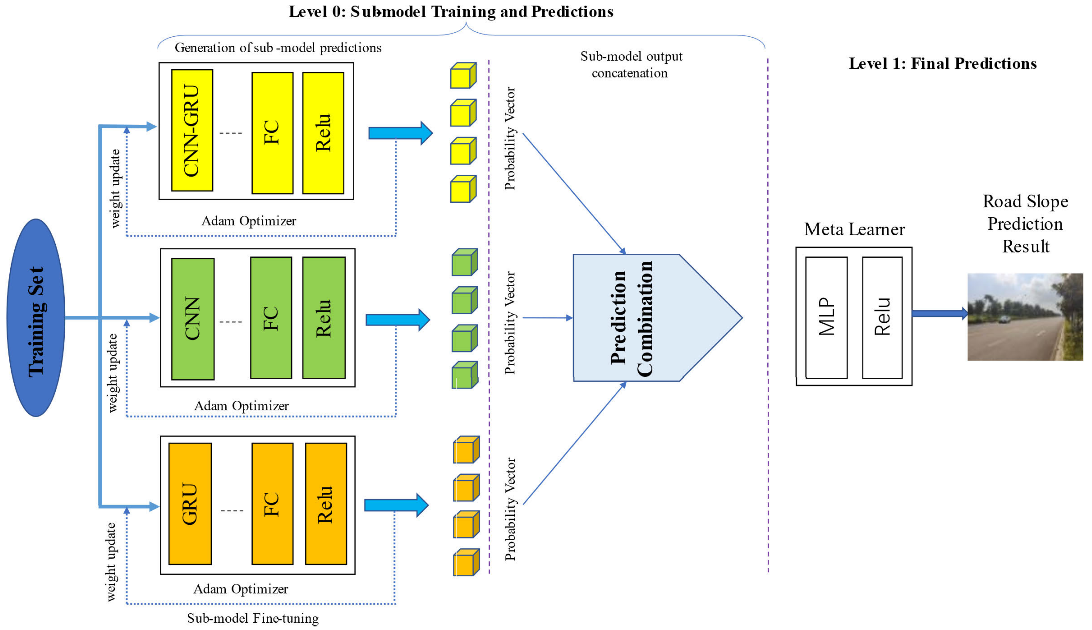

FIGURE 1. Stacking model structure.

TABLE 1. Vehicle parameters.

Vehicle	Dimension mm	4110X1750X1583
	Maximum speed km/h	125
	Vehicle Mass kg	1480
	Tire specification	205/50 R16
Electric motor	Type	Permanent magnet synchronous motor
	Maximum power kw	80
	Maximum torque Nm	230
Battery	Type	Ternary Li-ion Battery
	NEDC Pure electric range km	318

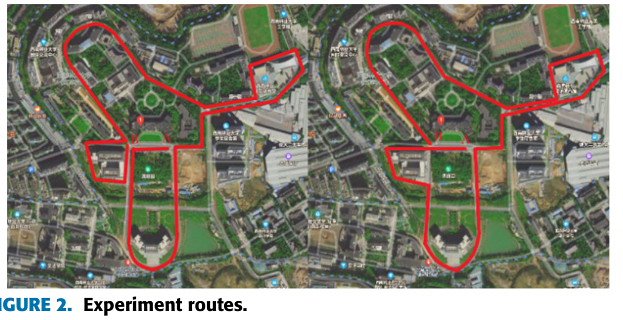

FIGURE 2. Experiment routes.

SD card, and high-precision IMU (Inertial Measurement Unit). The T-box terminal collects the CAN bus data of the car at a sampling frequency of 10 HZ through the OBD (On-Board Diagnostics) module and MCU (Microcontroller Unit). InVIEW is used as the data analysis and processing software, which reads the real-time vehicle information acquired by the T-BOX in the SD card. Python is used to build algorithm model and produce results by inputting test data into algorithm model. The slope data gathered by the high-precision IMU is utilized to calculate the real value of the road grade.

B. EXPERIMENT SECTION AND DATA PROCESSING

In order to better demonstrate the performance of the algorithm and better match the actual road conditions, a road section with uphill, downhill, flat, straight, and curved multiple road conditions were selected as the test verification section. Fig. 2 shows the test verification routes. In the test, the vehicle was driven along the test section for 2 laps. The first lap is shown on the left side of Fig 2, and the vehicle driving from point A to point B along the red line. The second lap is shown on the right side of Fig 2, and the vehicle driving from point B to point A along the red line. Total mileage is 5.48km, the average speed is 20.74km/h, and the maximum speed is 36.48km/h. The vehicle starts from point A, while the recorder starts to record data. The vehicle travels 2 laps and reaches point A and stops recording data. Marking by the recorder when the vehicle reaches point B to distinguish the first and second lap. The data from 2 laps of the vehicle are used as the test set and the data from the first lap are used as the training set. The experimental test set input data are shown in Fig. 3.

The slope estimation method at the current moment is similar to the traditional table prediction. The slope estimation value is obtained by the data input at the current moment. The input feature data and label data of the training set are sliced according to the data sampling time during data processing,

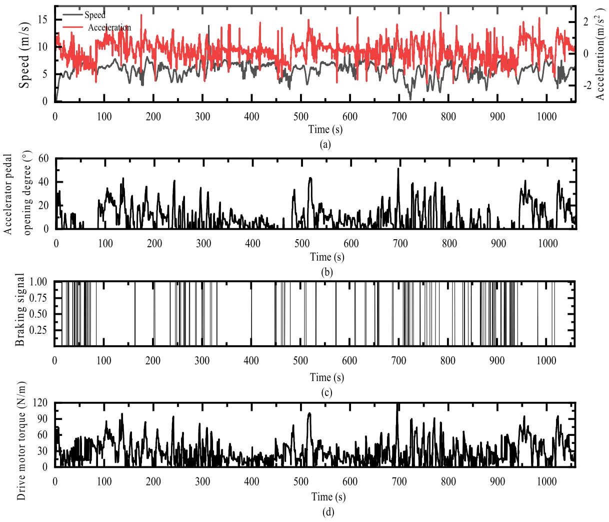

FIGURE 3. Input data for the test set.

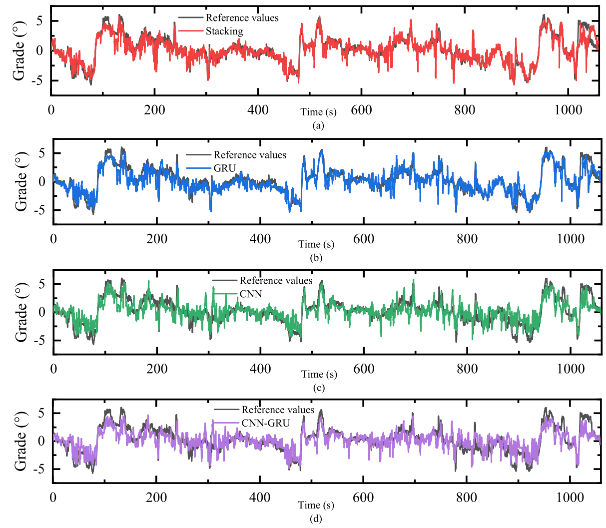

FIGURE 4. Current moment estimation results of road slope.

TABLE 2. Estimation results error indicators.

	f_{RMSE}/°	MAE/°	R
STACKING	0.900	0.581	0.920
GRU	1.006	0.687	0.899
CNN	1.384	1.070	0.800
CNN-GRU	1.356	1.049	0.805

and the training set is disturbed during model training to increase model training accuracy.

Neural networks forecast the slope values at future dates in a time-series way, in contrast to sensor-based or longitudinal dynamics-based slope estimation approaches. The data length of 2s, 3s, and 4s is utilized as the window length while processing the training set data to divide the feature data and label data and predict the next slope values of 2s, 3s, and 4s by producing the data of the window length. Unlike the table prediction in order to prevent the leakage of future information in the model training in accordance with the time series without disrupting the training set.

IV. RESULTS AND ANALYSIS

A. ANALYSIS OF CURRENT SLOPE ESTIMATION RESULTS

In order to evaluate the estimation performance of the algorithm, the estimation results of the proposed algorithm are compared with the results of GRU, CNN, and CNN-GRU. Fig. 7 shows the comparison graph of the estimation results, and f_{RMSE} (root mean square error), MAE (mean absolute error), and R (Pearson correlation coefficient) are chosen as the error indicators. The error indicators of the estimation results at the current moment are listed in Table 2.

The error indicators are expressed as follow:

$$f_{\mathrm{RMSE}} = \frac{\sqrt{\sum_{t=1}^{N}(X_t - Y_t)^2}}{N} \tag{6}$$

$$MAE = \frac{\sum_{t=1}^{N}|X_t - Y_t|}{N} \tag{7}$$

$$R = \frac{N(\sum_{t=1}^{N} X_t \cdot Y_t) - ((\sum_{t=1}^{N} X_t)(\sum_{t=1}^{N} Y_t))}{\sqrt{(N(X_t^2 - \sum_{t=1}^{N} X_t)^2) \cdot (N(Y_t^2 - \sum_{t=1}^{N} Y_t)^2)}} \tag{8}$$

where X_t is Estimated value at moment t, Y_t is Measured values at moment t, N is Total amount of data.

As shown in Fig. 4, the four models can fit the real value better in both known and unknown road sections. The conventional slope estimation method based on longitudinal dynamics cannot accurately estimate the slope value during braking due to the influence of torque variation and other factors. The stacking model can include the braking signal in the input parameters, so it can still estimate the slope better when the vehicle is braking. The R values of all four algorithms shown in Table 2 are greater than 0.8, which indicates that the estimated results are strongly correlated with the true values. The stacking model has the highest correlation and the lowest f_{RMSE} and MAE compared to other single models, which implies that the stacking model has higher estimation accuracy because the stacking model can weigh the estimation performance of every single model to reach the best estimation result. In the single model, GRU has a lower error and higher correlation compared to CNN and CNN-GRU. The possible reason is that GRU can pass the information from the current moment to the next moment and fully use historical information in estimating the current road slope value, so it has better estimation results for time-varying parameters like slope. Its error index is closer to the stacking model f_{RMSE}, the MAE difference is about 0.1°, and the R difference is 0.021, which also means that GRU has a higher weight in the stacking model. The correlation between the CNN and CNN-GRU estimation results is relatively similar with only a 0.05 difference, and the difference between f_{RMSE} and MAE

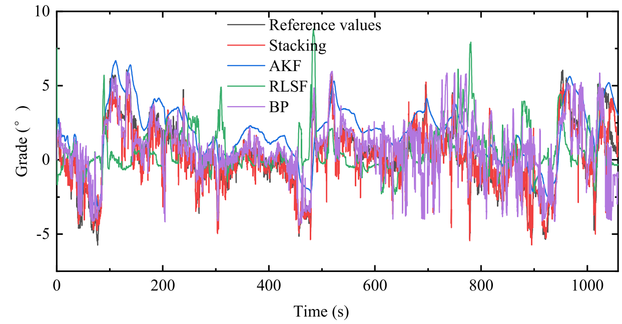

FIGURE 5. Comparison chart of the road slope estimated results at the current moment.

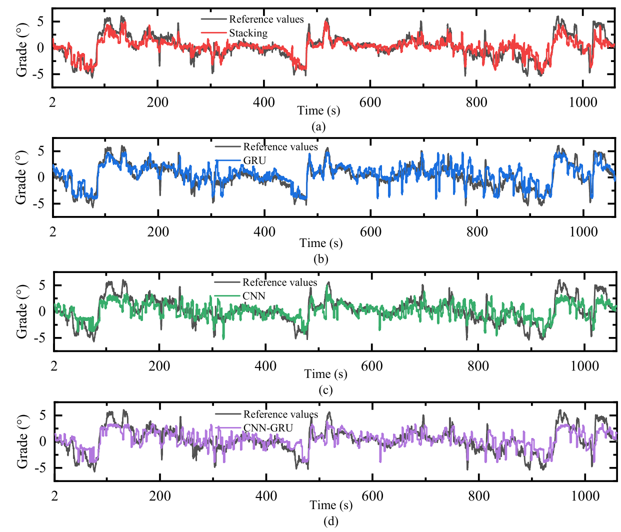

FIGURE 6. Future 2s prediction results of road slope.

is only 0.028° and 0.021°, which is because CNN-GRU adds memory information to CNN feature extraction to improve the accuracy. CNN, CNN-GRU, and stacking model errors are much higher than GRU and integrated model errors. f_{RMSE} differs by 0.484°, 0.456°, *MAE* differs by 0.489°, 0.468°, and the difference of *R* is 0.120°, 0.125°, which is due to CNN can extract data features adaptively, and the regularity feature of road slope feature change is not obvious in some road sections with rapid slope change.

In order to reflect the advantages of this model over the traditional algorithm, the estimation results of this model are compared with the AKF (Adaptive Kalman Filter), RLSF (the Recursive Least Squares with Forgetting factor) and BP (Back Propagation Neural Network). the comparison results are shown in Fig. 5. In comparison to AKF, RLSF and BP, the stacking model in the figure has the highest degree of fit to the true value. RLSF as a stable variable estimating approach, while adding an oblivion factor to the recursive least squares, is still not ideal for time-varying parameter estimation. AKF estimation results are closer to the true value, but there are numerous brakes due to the experimental process, and the influence of the filter's response speed leads to larger errors. BP, as a local search optimization method, is likely to fall into local extremes, and the "sawtooth phenomenon" occurs when optimizing complex objective functions, thus making the algorithm inefficient. In summary, this stacking model

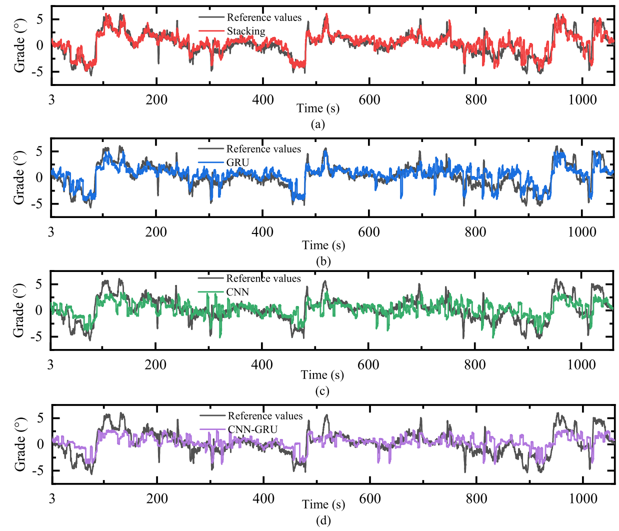

FIGURE 7. Future 3s prediction results of road slope.

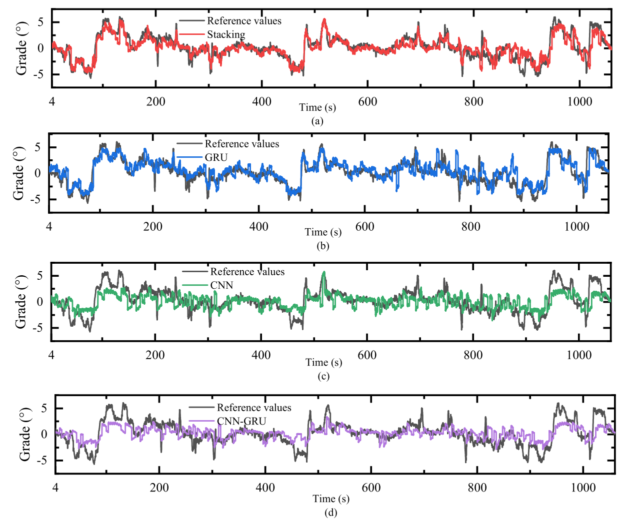

FIGURE 8. Future 4s prediction results of road slope.

estimates the slope more accurately than other single models and conventional methods, providing a more accurate assessment of the slope at present. All input parameters of the model are derived from the vehicle CAN bus without adding additional sensors, and the model prediction and training are separate for the entire test set, which can be computed within 0.1s, reducing equipment and computational costs in practice.

B. ANALYSIS OF SLOPE PREDICTION RESULTS FOR FUTURE MOMENTS

The prediction results of stacking model are also contrasted with those of GRU, CNN, and CNN-GRU for the prediction of the future moment slope. Fig. 6-8 show the slope estimation results for the future 2s, 3s, and 4s. Table 3 shows the error indicators of the slope estimation results for the future 2s, 3s, and 4s.

As shown in Fig. 6-8, both the stacking model and GRU can fit the true value better, however, CNN and CNN-GRU have large errors in the first 150s, 450s-480s, and later 250s.

TABLE 3. Prediction result error indicators.

		f_{RMSE}/°	*MAE*/°	*R*
2s	STACKING	1.262	0.916	0.840
	GRU	1.437	1.098	0.806
	CNN	1.711	1.308	0.658
	CNN-GRU	1.673	1.262	0.684
3s	STACKING	1.252	0.915	0.851
	GRU	1.413	1.085	0.807
	CNN	1.874	1.414	0.575
	CNN-GRU	1.857	1.411	0.579
4s	STACKING	1.237	0.876	0.841
	GRU	1.370	1.005	0.809
	CNN	1.913	1.455	0.543
	CNN-GRU	1.878	1.420	0.571

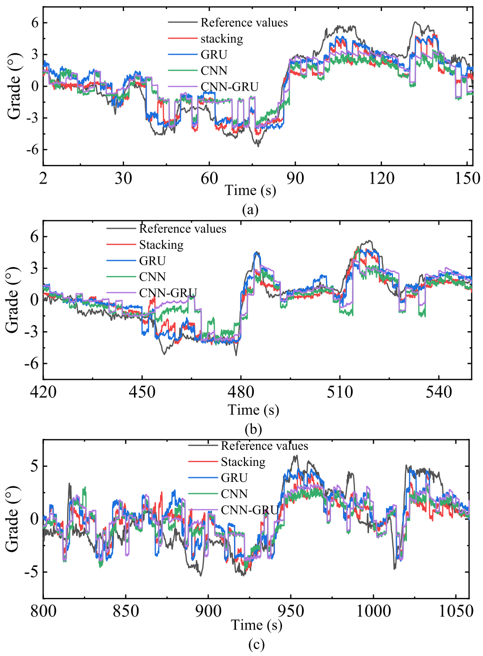

FIGURE 9. Partial enlargement of future 2s prediction results of road slope.

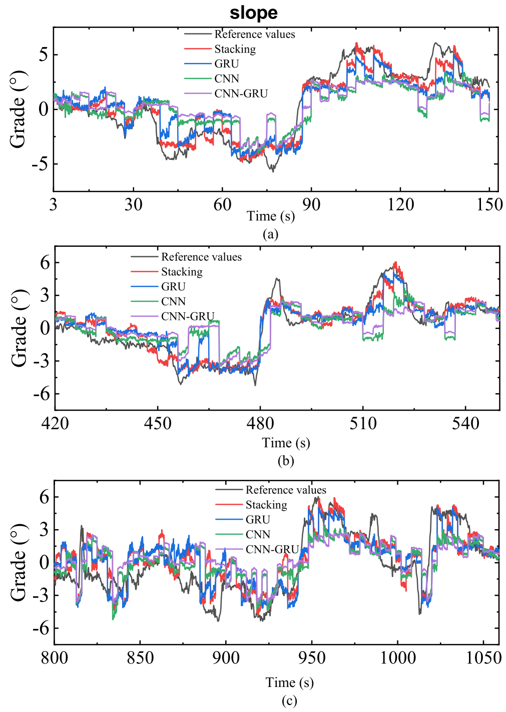

FIGURE 10. Partial enlargement of future 3s prediction results of road slope.

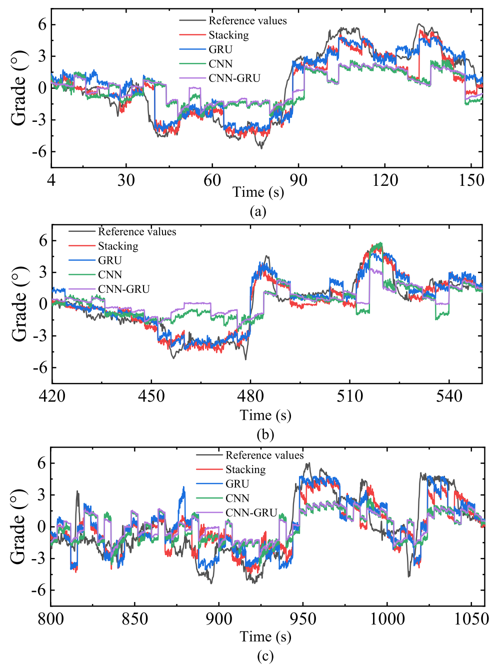

FIGURE 11. Partial enlargement of future 4s prediction results of road slope.

When the slope value changes rapidly in a short period of time in the road section, the error magnification of the three time periods is shown in Figs. 9-11. This may be since the road slope features of these road sections are not obvious and the convolution scales the data by dot product operation to extract features adaptively, this process also ignores some other features of the data. CNN, CNN-GRU is better at extracting the slope features when the slope changes smoothly than when the slope changes rapidly, and its prediction in the smooth road sections results are close to the real values.

As shown in Table 3, the training procedure for the future 2s, 3s, and 4s did not disturb the data set in order to prevent information leaking, which increased each model's prediction error when compared to the results of the current moment's estimation. The f_{RMSE} and *MAE* values of GRU fall with increasing prediction time, while the R value grows. The reason is that as the prediction time and data input to the model rise at each step, GRU can mix more data information with the present information to improve prediction accuracy. The f_{RMSE}, *MAE*, and *R* values of CNN, CNN-GRU increase with increasing prediction time because the point multiplication process ignores more features as the input data increases and has a more significant impact on the prediction results for rapid changes in slope. The stacking model's prediction results are more stable, with minimal variance in error indications. As the prediction time increases, the f_{RMSE} of the stacking model decreased by 0.010° and 0.015° relative to the previous group, *MAE* decreased by 0.001° and 0.039° relative to the previous group, with the lowest variation among the models. However, the R-value of the stacking model is the highest when predicting the future 3s, which may be due to the following reasons: According to the change in error metrics, the maximum f_{RMSE} and *MAE* changes of CNN and CNN-GRU are 0.184°, and the minimum is 0.106° as the estimate duration grows from 2s to 3s. The maximum f_{RMSE} and *MAE* changes of CNN and CNN-GRU are 0.006°, and the minimum is 0.041° as the estimation time grows from 3s to 4s. The stacking model enhances the weight of the prediction results of the CNN and CNN-GRU models since the error of CNN and CNN-GRU models grows dramatically in the smooth slope section while the error of GRU increases with the rise in prediction time. In summary, the stacking model can better predict the road slope in the future 2s, 3s and 4s.

V. CONCLUSION

In this paper, a stacking model based on GRU, CNN, and CNN-GRU is proposed. The model integrates the advantages of GRU memory history information and CNN feature extraction and obtains the best estimation result by estimating the weight of each base model. This method only uses the CAN bus data to predict the road slope with the applicability of low cost and low computational time. Adding a braking sign to the model input improves the estimation performance of the vehicle during braking. The processing of the input data estimates the present time and forecasts the road slope values of the 2s, 3s, and 4s slopes in the future.

Experiments demonstrate that the model performs well in both known and unknown road sections. The correlation coefficient between the predicted value and the real value of the model at the current time and the future time is greater than 0.840 (representing a strong correlation), and the f_{RMSE} and *MAE* values are the smallest compared to the estimated results of each base model. The stacking model currently has the lowest f_{RMSE} and *MAE* values when compared to the results of future time prediction. In the prediction of slope at future moments, the f_{RMSE} and *MAE* values grow with prediction time, each time within 0.02° and 0.1°, respectively. The weight of each base model shifts as the prediction time grows, which results in the highest correlation coefficient between the predicted and true values in the future 3s. In summary, this model can better estimate the current moment slope value and predict the slope value for a short time in the future and provide a new parameter prediction method for intelligent control of electric vehicles, unmanned driving, and forward-looking control of vehicles.

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