

The Prediction model for Road Slope of Electric Vehicles Based on Stacking framework of deep learning

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ABSTRACT

For the vehicle's control, stability, and comfort while driving, it is essential to have accurate real-time information about road slopes and the ability to predict future moment gradient values. Consequently, this research suggests a stacking model approach to estimating electric vehicle road slopes. With Multilayer Perceptron (MLP) serving as the meta-classifier, the basis classifiers include Gated Circulation unit (GRU), Convolutional Neural Network (CNN), and CNN-GRU. To choose the right parameters to train the base classifier with, we look at the equations describing the vehicle's dynamics. In order to train the meta-classifier, the basic classifier uses its estimated findings. Slicing the training set by data sampling time and windowing it to forecast the future slope values in 2s, 3s, and 4s yields the current slope values. We choose error indicators for assessment after conducting road testing. In order to estimate the current moment slope, the stacking model is tested against each base classifier, Adaptive Kalman filter, Recursive Least Squares with Forgetting Factor, and Back Propagation Neural Network. The results show that the stacking model fares better than the traditional algorithm. When looking at the outcomes that each base classifier predicted for future time slope prediction, we can see that the stacking model outperforms them for the short-term future.

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]. 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 [11-13] (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 [16-19], 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, 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].

LITERATURE REVIEW

IN “A REVIEW ON ELECTRIC VEHICLES: TECHNOLOGIES AND CHALLENGES. SMART CITIES” Electric Vehicles (EVs) are gaining momentum due to several factors, including the price reduction as well as the climate and environmental awareness. This paper reviews the advances of EVs regarding battery technology trends, charging methods, as well as new research challenges and open opportunities. More specifically, an analysis of the worldwide market situation of EVs and their future prospects is carried out. Given that one of

the fundamental aspects in EVs is the battery, the paper presents a thorough review of the battery technologies—from the Lead-acid batteries to the Lithium-ion. Moreover, we review the different standards that are available for EVs charging process, as well as the power control and battery energy management proposals. Finally, we conclude our work by presenting our vision about what is expected in the near future within this field, as well as the research aspects that are still open for both industry and academic communities. The automotive industry has become one of the most important world-wide industries, not only at economic level, but also in terms of research and development. Increasingly, there are more technological elements that are being introduced on the vehicles towards the improvement of both passengers and pedestrians' safety. In addition, there is a greater number of vehicles on the roads, which allows for us to move quickly and comfortably. However, this has led to a dramatic increase in air pollution levels in urban environments (i.e., pollutants, such as PM, nitrogen oxides (NOX), CO, sulfur dioxide (SO₂), etc.). In addition, and according to a report by the European Union, the transport sector is responsible for nearly 28% of the total carbon dioxide (CO₂) emissions, while the road transport is accountable for over 70% of the transport sector emissions [1]. Therefore, the authorities of most developed countries are encouraging the use of Electric Vehicles (EVs) to avoid the concentration of air pollutants, CO₂, as well as other greenhouse gases. More specifically, they promote sustainable and efficient mobility through different initiatives, mainly through tax incentives, purchase aids, or other special measures, such as free public parking or the free use of motorways. EVs offer the following advantages over traditional vehicles:

- Zero emissions: this type of vehicles neither emit tailpipe pollutants, CO₂, nor nitrogen dioxide (NO₂).

IN “ROAD SLOPE ESTIMATION BASED ON ACCELERATION ADAPTIVE INTERACTIVE MULTIPLE MODEL ALGORITHM FOR COMMERCIAL VEHICLES.”

Road slope is an important external variable in vehicle dynamic control systems. However, it is a challenging problem to estimate road slope accurately for commercial vehicles due to the coupling problem among the mass, road slope and pitch angle. To solve this problem, a novel road slope estimation scheme with the correction of pitch angle is proposed. First, the coupling problem between road slope and body pitch is analyzed from the perspective of sensor signals. Next, the driving conditions are divided into gentle and strong scenarios, abstracted to the smooth driving model (SDM) and intensive driving model (IDM), respectively. SDM alone cannot guarantee accuracy under intensive scenarios, while IDM alone converges slowly under smooth driving scenarios. The acceleration adaptive interactive multiple model (AAIMM) algorithm is then designed to combine the models and determine which model is the most

appropriate under different driving intensities. At last, the sensor-less pitch angle correction strategy based on the suspension deformation model is presented and the particle swarm optimization (PSO) algorithm is used to optimize the suspension stiffness off-line. The simulations and road tests indicate the effectiveness and accuracy of the proposed road slope estimation scheme. Road slope is one of the most significant parameters for modern vehicle controllers because the slope angle can influence the vehicle's longitudinal dynamics considerably. For example, transmission shift scheduling system needs online road slope estimation to enhance comfort and reliability [1]. The adaptive cruise control system (ACC) requires accurate road slope information to achieve the required performances of power and economy [2]. Road slope information can also be used for three-dimensional map creation [3]. On account of the complex road conditions for commercial vehicles, the slope information is more important for the controllers of commercial vehicles. Current road slope estimation methods can be divided into the indirect methods and direct methods.

EXISTING SYSTEM

The recently emerging multi-mode plug-in hybrid electric vehicle (PHEV) technology is one of the pathways making contributions to decarbonization, and its energy management requires multiple-input and multipleoutput (MIMO) control. At the present, the existing methods usually decouple the MIMO control into singleoutput (MISO) control and can only achieve its local optimal performance. To optimize the multi-mode vehicle globally, this paper studies a MIMO control method for energy management of the multi-mode PHEV based on multi-agent deep reinforcement learning (MADRL). By introducing a relevance ratio, a hand-shaking strategy is proposed to enable two learning agents to work collaboratively under the MADRL framework using the deep deterministic policy gradient (DDPG) algorithm. Unified settings for the DDPG agents are obtained through a sensitivity analysis of the influencing factors to the learning performance. The optimal working mode for the hand-shaking strategy is attained through a parametric study on the relevance ratio. The disadvantage of the proposed energy management method is demonstrated on a software-in-the-loop testing platform. The result of the study indicates that the learning rate of the DDPG agents is the greatest influencing factor for learning performance. Using the unified DDPG settings and a relevance ratio of 0.2, the proposed MADRL system can save up to 4% energy compared to the single-agent learning system and up to 23.54% energy compared to the conventional rule-based system.

Disadvantages

- The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets to detect Road Slope of Electric Vehicles.
- Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.
- Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.

Proposed System

In the proposed system, 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 this system.

Advantages

- In this paper, GRU, CNN, and CNN-GRU are selected as the base classifiers, and MLP is chosen as the meta classifier.

The multi-model technique with machine learning necessitates sophisticated decoupling calculations, and the estimation results are influenced by modeling accuracy and still contain large mistakes when the car is braked

Conclusion

This study proposes a stacking model that combines GRU, CNN, and CNN-GRU. The model estimates the weight of each base model to produce the optimum estimation result, integrating the benefits of GRU memory history information with CNN feature extraction. In order to forecast the road's slope, this system relies only on CAN bus data, which is both inexpensive

and computationally efficient. The vehicle's estimating performance while braking is enhanced by including a braking cue in the model input. After running the numbers through their paces, the system predicts the future values of the 2s, 3s, and 4s road slopes and provides an estimate of the current time. Results show that the model works effectively on both familiar and unfamiliar road segments. In addition to the least fRMSE and MAE values relative to the estimated outcomes of each base model, the correlation coefficient between the projected value and the true value of the model at both the present and future times is more than 0.840, indicating a significant correlation. When comparing the results of future time prediction with the stacking model, the former presently has the lowest values for fRMSE and MAE. The fRMSE and MAE values increase each time within 0.02° and 0.1° , respectively, in the prediction of the slope at future occasions. For the next three years, the projected and actual values will have the strongest association since the weight of each base model changes as the forecast time increases. To summarise, this model offers a novel way for predicting parameters that may be used for intelligent control of electric vehicles, autonomous driving, and cars that can gaze into the future, as well as for better estimating the present instant slope value.

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