2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
October 14-18, 2024. Abu Dhabi, UAE

An LSTM-based Model to Recognize Driving Style and Predict Acceleration

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***Abstract*— To ensure safe cooperative driving in mixed traffic with both manned and unmanned vehicles, it is crucial to understand and model the driving styles of human drivers. This paper explores how to develop accurate recognition of driving style and use that for the prediction of vehicle motion, which enables better performance in cooperative driving. A simulation testbed that consists of a driving simulator and a copilot is first introduced for the purpose of data collection and testing. A Long Short-Term Memory (LSTM)-based network that models human driving styles and predicts driving acceleration is developed. Standalone tests are conducted to examine the model performance in the simulation testbed. Finally, the model is evaluated in a series of merging experiments that involves 5 vehicles.**

I. Introduction

In recent years, the exploration of cooperative driving among autonomous vehicles (AVs) has attracted significant interest in transportation research. Various projects, such as the California PATH project [1], CHAUFFEUR project [2], SARTRE project [3], and Energy ITS project [4], have studied cooperative driving, aiming to enhance safety, mobility, and environmental sustainability through innovative technological solutions. This paradigm shift towards cooperative driving, facilitated by vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, holds immense promise for revolutionizing the landscape of modern transportation systems. However, the interaction between AVs and the existing fleet of human-driven vehicles presents a great challenge that demands fresh perspectives. While existing projects have significantly contributed to our understanding of cooperative driving among AVs, the integration of human-driven vehicles adds a layer of unpredictability that requires careful consideration.

Human drivers exhibit a wide array of actions influenced by individual preferences, situational factors, and traffic conditions. To effectively capture this intricate diversity, the fusion of predictive models emerges as a compelling strategy. While human behavior exhibits an inherent element of randomness, it is equally characterized by distinct patterns, notably in the form of habits. Human drivers' actions are not entirely arbitrary. Temporary driver habits, such as regularly checking mirrors, using turn signals, maintaining appropriate following distances, and monitoring blind spots, contribute to heightened situational awareness and predictability on the road. Moreover, these driving habits are closely tied to a driver's overall driving style, which is critical for driving safety, energy conservation, emissions reduction, and driving assessment [5]. For instance, a driver exhibiting distracted behavior tends to engage in fewer mirror checks and may struggle to maintain proper following distances. Recognizing these specific driver habits becomes feasible with access to comprehensive data, rendering the identification of the driver's driving style attainable.

Reflecting a driver's behavioral habits and decisions while operating a vehicle, driving style can inherently manifest in both long-term and short-term patterns. Short-term driving style is discerned through the analysis of behavior in specific, immediate driving scenarios, such as how a driver executes a lane change or responds to adjacent vehicle's lane merge. This style is highly influenced by environmental factors such as adjacent vehicles' distance and speed, as well as internal factors including the vehicle data and the driver's intention. The variability of short-term driving style makes it flexible in real-time driving decisions. In contrast, long-term driving style emerges from the observation of driving behaviors over extended periods, capturing the consistent habits and preferences that characterize a driver's overall approach to driving. This style is less about the reaction to certain scenario instances and more about the overall and continuous short-term driving styles based on the long-term observations of driving behaviors.

Furthermore, the knowledge of a driver's specific driving style makes it possible to more accurately predict the driver's subsequent driving actions and consequently the vehicle's motion. Within the realm of recognition and predictive modeling, Long Short-Term Memory (LSTM) networks [6] offer a potent tool for capturing the temporal dynamics inherent in human driving decisions. LSTM, as a specialized form of recurrent neural network (RNN) [7], excels at capturing sequential patterns and dependencies. This capacity is well-suited to the task of modeling driving behaviors, which are inherently sequential and contextually contingent. By leveraging LSTM's ability to retain and propagate information across varying time steps, a cooperative driving system can discern not only the immediate actions of road users but also the historical context that informs these actions.

This paper has the following contributions: First, it introduces a simulation testbed designed for cooperative driv-

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This work is supported by the National Science Foundation (NSF) Grants CPS 2212582 and TI 2329852.

ing within mixed traffic environments. Second, it proposes an LSTM-based model optimized for recognizing human drivers' driving style and predicting the movements of human-driven vehicles. Third, it assesses the efficacy of the proposed method through offline and online experiments within specific scenarios. Finally it conducts a comparative analysis of the proposed approach against other existing methods in mixed traffic driving involving 5 vehicles.

This paper is organized as follows. Section II introduces the related work of this project. Section III provides an overview of both the hardware architecture and the software framework of the simulation testbed platform. Section IV describes the proposed LSTM recognition and prediction models. Section V presents detailed experiments and their outcomes. We conclude the paper and outline the future research in Section VI.

II. Related Work

In recent years, the field of cooperative driving for automated vehicles has witnessed significant advancements through various research endeavors. Notable projects include the California PATH project [1], which enabled multiple automated vehicles to engage in platooning within an Intelligent Vehicle Highway System. The CHAUFFEUR project [2] implemented Automated Highway Systems on European motorways, while the SARTRE project [3] focused on platooning for both trucks and cars. While these existing projects have significantly improved the performance of AVs in cooperative driving scenarios, they have primarily focused on interactions among AVs. The cooperation between autonomous and human-driven vehicles poses unique challenges due to the inherent uncertainty and unpredictability of human driving behaviors. However, in recent years, there has been a growing acknowledgment of the need to address cooperative driving involving both autonomous and human-driven vehicles. For instance, Xie *et al.* proposed two cooperative driving strategies for AVs operating in heterogeneous traffic with the goal of stabilizing traffic flow [8]. They emphasized the necessity for further research in developing cooperative driving strategies that incorporate the predictions of human-driven vehicles' behavior. Valiente *et al.* developed a Multi-agent Reinforcement Learning (MARL) algorithm with a decentralized framework and a reward function, allowing AVs to learn from interactions with human-driven vehicles [9]. Mosharafian *et al.* introduced a Cooperative Adaptive Cruise Control (CACC) system employing a hybrid stochastic predictive approach for lane changes within mixed traffic conditions [10] [11]. In essence, cooperative driving involving both autonomous and human-driven vehicles is still in its early stages. To effectively address the challenges posed by this coexistence, it becomes imperative to equip human-driven vehicles with intelligent driving assistance systems, V2V communication capabilities, and accurate models for understanding human drivers.

A driver's driving style serves as a pivotal component in both comprehending human drivers and advancing intelligent vehicle control systems. It stands as a fundamental cornerstone for the development of advanced driver assistance systems (ADAS) [12]. Qi *et al.* underscored the importance of building human-centered intelligent transport systems, emphasizing the need for a profound understanding of the diverse driving styles exhibited by individuals. To facilitate this understanding, they proposed a three-layer driving style structure, wherein the driving style determines driving states, which subsequently influence driving behaviors [13]. Mehmet *et al.* introduced an innovative LSTM-based model capable of recognizing a driver's unique driving characteristics without explicit labeling [14]. This marks a significant step toward understanding driving styles. Saleh *et al.* proposed a stacked-LSTM classification model that takes into account both ego vehicle data and surrounding vehicle information as inputs, categorizing drivers into distinct driving styles including normal, aggressive, and drowsy [15]. Li *et al.* introduced an image-based driving style classification method, comparing the performance of CNN, LSTM, and pretrain-LSTM models, categorizing driving styles into low-risk, moderate-risk, and high-risk [16]. Nevertheless, recognizing driving style is not a straightforward task, as it constitutes a concealed aspect of human personality. Since driving styles are more observable when drivers respond to certain scenarios, the external environmental information plays an equally significant role as the ego vehicle data. A holistic approach that considers comprehensive data sources is therefore necessary.

Predicting the trajectories of surrounding vehicles has gained attention due to its relevance in enhancing road safety, improving traffic management, and advancing AV technologies. Yang *et al.* developed a social convolutional pooling LSTM network with an attention mechanism for behavior prediction on the expressway [17]. However, with the rapid advancement in V2V and V2I communication, predicting the ego vehicle's trajectory becomes more reliable and advantageous by accessing shared vehicle data. Mozaffari *et al.* conducted an investigation on the problem of trajectory prediction and reviewed the most recent deep learning-based solutions [18]. They concluded that one of the main research gaps is that the input to the model in most existing works is not sufficient. Kim *et al.* proposed an LSTM-based network for driving style recognition and trajectory prediction [19]. To predict the ego vehicle's trajectory, they classified the driving styles while the past trajectory of the ego vehicle was considered as the input. Tian *et al.* developed a personalized trajectory prediction method for high-speed trains considering different driving styles with the help of V2V communication and an LSTM network [20]. In conclusion, to facilitate accurate trajectory prediction, it is crucial to consider a comprehensive set of data, including not only the ego vehicle data, driver's intention and driver's driving style, but also the environmental information.

III. System Architecture

As shown in Figure 2, our cooperative driving testbed integrates a driving simulator and a copilot which convert a traditional human-driven vehicle into an intelligent human-

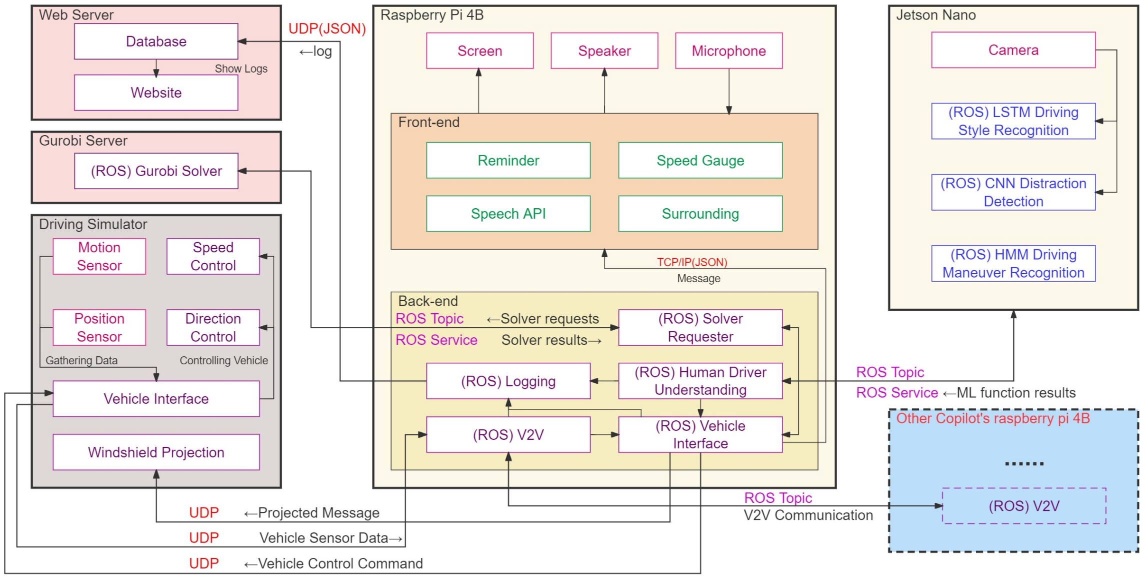


Fig. 1: Software Architecture of the cooperative driving testbed.

Fig. 2: The cooperative driving testbed setup.

Fig. 3: The simulated windshield projection system (middle) and the visual display of the current speed and the desired speed (bottom right).

driven vehicle (IHV). The copilot consists of a touch screen, a speaker, a camera, a microphone, and two embedded microcomputers (a Raspberry Pi 4B and an NVIDIA Jetson Nano). The driving simulator offers a multi-monitor configuration that features in-vehicle perspectives, real-time data visualization, and tactile feedback from the Logitech G290 driving force suite. The Carnetsoft driving simulator [21] consists of a comprehensive road map database, a script-driven programming language, and interfaces for external devices. Integrated within the central monitor is a transparent text window, akin to modern windshield projection systems. This interface provides feedback and instructional messages to the driver. For instance, it can alert the driver the intentions of adjacent vehicles seeking to merge, as shown in the middle of Figure 3.

The cooperative driving testbed's software adopts a client-server architecture, as shown in Figure 1. Communication and scheduling packages run on the Raspberry Pi which facilitate efficient coordination among system components. Central to the system's functionality, the machine learning modules within the Jetson Nano assume a crucial role in providing driver monitoring services. The Jetson Nano hosts the LSTM model which recognizes driving styles and makes predictions. On a separate server computer, the Gurobi server [22] utilizes mathematical optimization to provide decision making services for cooperative driving.

IV. Methodology

A. Model Formulation

The driving style is the driver's regular habit of maneuvering the vehicle especially when dealing with specific situations. For instance, an aggressive driver may often display behaviors such as quick acceleration or sudden braking while merging into another lane. On the other hand, a conservative driver typically exhibits behaviors such as maintaining a steady pace and showing caution in braking during lane merging. Recognizing a driver's driving style is crucial for understanding his current behavior and predicting

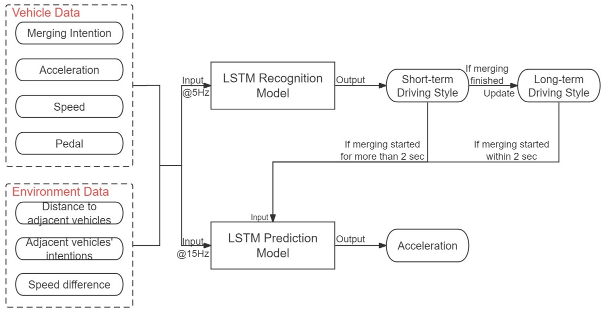


Fig. 4: Data flowchart of the model in lane-merging scenario.

his future behaviors. To effectively classify various driving styles, our model relies on a comprehensive set of input data. As depicted in Figure 4, the model considers a lane-merging scenario and takes into account two key sources of information: vehicle data and environment data.

The vehicle data consists of gas pedal percentage, brake pedal percentage, velocity, acceleration, and ego vehicle's merging intention, which are extracted from the driving simulator. Furthermore, our cooperative framework enables copilots to communicate and share their respective vehicle data. Upon receiving data from neighboring vehicles, the ego vehicle's backend can compute the environment data, which include the longitudinal distances between the ego vehicle and adjacent vehicles, the speed difference between the ego vehicle and adjacent vehicles, as well as the adjacent vehicles' merging intentions. The driving styles are classified into three types: aggressive, normal, and conservative.

The input data sequence of the recognition model, beginning at the start of the lane merging instance and continuing to the present, is sampled at a rate of 5Hz and fed into the model in real-time. The recognition model generates a probability distribution matrix, which characterizes the likelihood of the observed driving behavior being one of three types. To derive the probability distribution matrix, the final hidden state is fed into a subsequent fully connected layer to map the temporal features into the desired output format, which is then passed to the softmax function to obtain the probability distribution. The class with the maximum probability will then be selected as the identified driving style for the current lane merging instance.

In order to obtain the driver's long-term driving style, we combine the current recognition result and the cumulative driving recognition result. First, we calculate the driver's short-term driving style S_i at time step i by

$$S_i = 3P_{aggressive} + 2P_{normal} + 1P_{conservative}, \tag{1}$$

where $P_{aggressive}$, P_{normal}, and $P_{conservative}$ are the probability of the corresponding styles. Let us denote W_i as the weight that represents how the short-term recognition result S_{t-i} at time step $t-i$ influences the long-term recognition result C_t at time step t. Therefore, we have

$$C_t = \sum_{i=0}^{t} W_i S_{t-i}. \tag{2}$$

Let us denote r_i to be the ratio between the two consecutive weights

$$r_i = \frac{W_{i+1}}{W_i}. \tag{3}$$

Given the assumption that r_i converges to a static value r, we subsequently have

$$C_t = rC_{t-1} + (1-r)S_t, \tag{4}$$

which is used to update the cumulative driving style recognition result.

In addition to recognizing the driving style, another LSTM-based model for predicting the longitudinal acceleration is proposed. Similar to the recognition model, the prediction model takes vehicle data and environment data as input. Besides, the driving style recognition result is considered as the feature as well. In the first two seconds of each lane-merging instance, the long-term driving style C_t is fed into the prediction model. After two seconds, when the length of the input sequence for the recognition model is sufficient, the short-term recognition result S_t is sent to the prediction model as the input. The prediction model utilizes the Adams optimizer [23] along with the mean squared error (MSE) as the optimization criterion during training. Instead of starting from the beginning of the lane merging instance, the input data sequence is captured using a sliding window, with a frequency of 15Hz and a window size of 2 seconds. Subsequently, the model generates the predicted acceleration for future intervals of 0.8 seconds, which can be used to calculate the predicted longitudinal speed.

B. Data collection

To acquire data and evaluate the model performance, we examine cooperative driving in a lane-merging scenario, which involves a group of five vehicles: one is an IHV controlled by a human driver and the rest are AVs. The IHV maintains its initial position within the middle lane. Two AVs cruise in the middle lane—one ahead and the other trailing, while two more AVs drive in the left lane. The front AV in the left lane intends to merge into the middle lane. The AVs are controlled by a Model Predictive Control approach that utilizes the Gurobi server to generate optimal solutions for each AV [24].

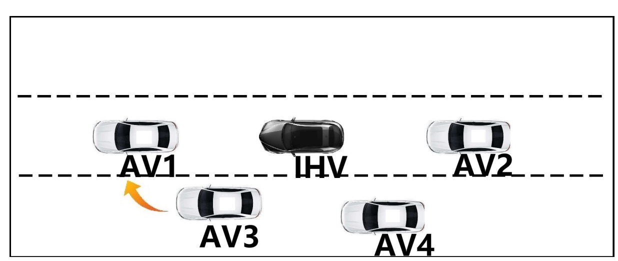


Fig. 5: Initial scenario setting.

In the data collection process, 5 volunteers were engaged in a series of tests over the course of one hour. Before the commencement of each scenario, a driving instruction would be projected onto the windshield. This message served as a reminder to the driver, urging him to steer back to the middle lane and maintain a steady speed of 60 km/h. Once the driver was ready, a subsequent message would appear, indicating the commencement of the next scenario. This message was accompanied by a countdown timer, set at 5 seconds. The data collection experiment yielded a comprehensive dataset, which is collected from 500 lane-merging trials. The dataset is split into a training set and a testing set with a 4:1 ratio. Recognizing that the objective of recognizing driving styles hinges on acquiring an accurate and generalized model for predictive purposes, we proactively consulted with each volunteer by asking their insights on the specific actions they would typically undertake when adopting different driving styles. Based on the feedback, we formulated a comprehensive guideline outlining the expected driver behavior within each distinct driving style. For the aggressive driving style, drivers were encouraged to exhibit behaviors such as accelerating and slowing down suddenly and recklessly. In contrast, for the conservative driving style, drivers were encouraged to maintain sufficient distance between their vehicle and adjacent ones while preferring to slowing down more than speeding up. For the normal driving style, drivers intended to maintain a stable speed and react timely. Figure 6 presents the loss and accuracy during the training process of the recognition model. The offline test accuracy reaches 96%. Figure 7 shows the confusion matrix of the short-term recognition testing.

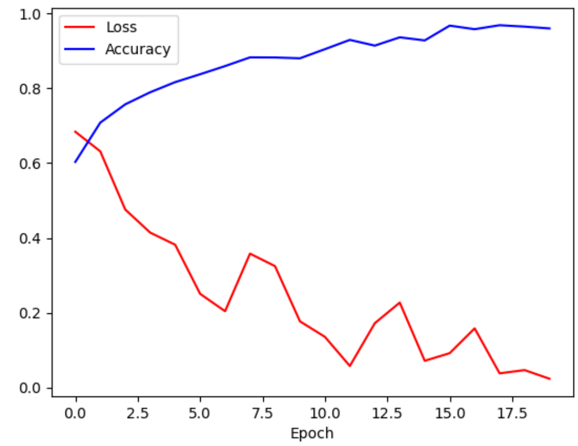


Fig. 6: Training results.

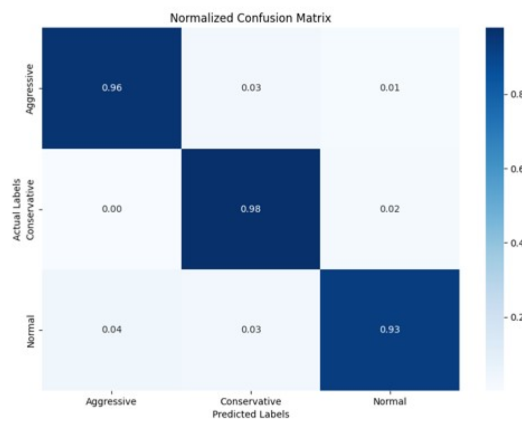


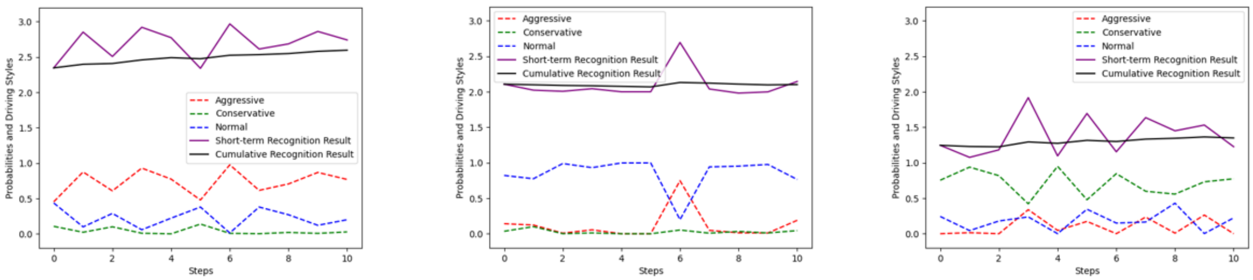
Fig. 7: Confusion matrix of the testing.

V. EXPERIMENT

In this section, experiments were conducted to evaluate the performance of driving style recognition and vehicle acceleration prediction in the lane merging scenario shown in Figure 5.

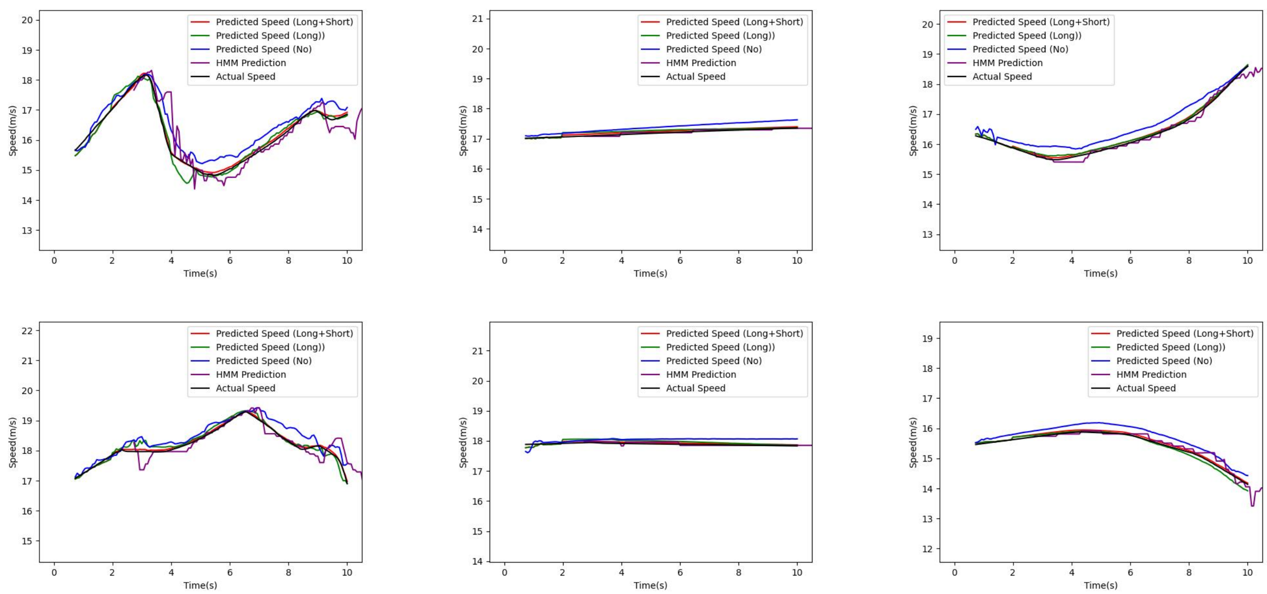
In order to validate the long-term recognition result, a volunteer conducted 3 sets of experiments, which include 10 consecutive tests with the same driving style, as shown in Figure 8. The dotted lines represent the probability of each driving style with different colors. The purple line represents the short-term recognition result S_t, while the black line represents the long-term recognition result C_t. In the sixth lane-merging instance of the normal driving style set, the driver was asked to perform aggressive driving style intentionally. It can be observed that the long-term recognition result still remains stable.

To further assess the model, we compare the model performance with different configurations and a Hidden Markov Model (HMM)-based baseline approach [25], as shown in Figure 9. For each driving style, we provide two examples. Figures in the left, the middle, and the right column show experiments from lane-merging instances of a driver with aggressive, normal, and conservative driving styles, respectively. In each figure, the black line shows the actual speed during the lane-merging instance. The red line demonstrates the predicted speed calculated based on the predicted acceleration obtained by the proposed prediction model. For comparison, the green line represents the result when we keep taking long-term recognition results as input instead of utilizing short-term recognition results after 2 seconds, and the blue line represents the result when we do not take any recognized driving style as input. The purple line shows the HMM-based acceleration prediction results for the comparison purpose. We can notice that the models with recognition results as input significantly outperform the model without them, while the model with different recognition results at different times obtain slightly better results than the model with long-term recognition results only, which is consistent with the statistical result. As shown in Table I, the Root Mean Square Error (RMSE) of the HMM-based prediction model is 0.9775 m/s^2, which is outperformed by the RMSE of the model without recognition result for each lane-merging instance (0.5841 m/s^2), The RMSE of the model with transitioning recognition results and with long-term recognition results only is 0.2768 m/s^2 and 0.3569 m/s^2, respectively. It can be observed that with the knowledge of the driving style recognition result, the prediction model obtained the most accurate results.



(a) aggressive (b) normal (c) conservative

Fig. 8: Comparison of long-term and short-term recognition results.



(a) aggressive (b) normal (c) conservative

Fig. 9: Prediction results with different model configurations.

TABLE I: Root Mean Squared Error (RMSE) of Testing Results for Single-Step Prediction.

Methods	$RMSE(m/s^2)$
$LSTM(Long + Short)$	0.2768
$LSTM(Long)$	0.3569
$LSTM(No)$	0.5841
HMM	0.9775

VI. Conclusion and Future Work

In this paper, we proposed an LSTM-based model that takes vehicle data and environmental information as input to recognize the driver's driving style, and utilize the knowledge of the driving style to further predict the vehicle's acceleration. Experimental results prove that incorporating comprehensive input data enhances the accuracy of driving style recognition, with long-term recognition showing stable performance as expected. Furthermore, the knowledge of the driving style significantly improves the accuracy of speed prediction.

In the future, we will enhance our algorithm to better understand human drivers, employing new methods for more accurate recognition and efficient data collection.

On the other hand, future work will also focus on model customization and adaptation. Although driving maneuvers may vary among different drivers, a particular driving style in a specific scenario tends to follow similar patterns. A model trained on data from multiple users could serve as an initial model for a new user. Over time, as the model continues to be used and further trained on that specific user's data, it would gradually become more customized and increasingly accurate.

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