End-to-end Multi-Modal Multi-Task Vehicle Control for Self-Driving Cars with Visual Perceptions

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***Abstract*—Convolutional Neural Networks (CNN) have been successfully applied to autonomous driving tasks, many in an end-to-end manner. Previous end-to-end steering control methods take an image or an image sequence as the input and directly predict the steering angle with CNN. Although single task learning on steering angles has reported good performances, the steering angle alone is not sufficient for vehicle control. In this work, we propose a multi-task learning framework to predict the steering angle and speed control simultaneously in an end-to-end manner. Since it is nontrivial to predict accurate speed values with only visual inputs, we first propose a network to predict discrete speed commands and steering angles with image sequences. Moreover, we propose a multi-modal multi-task network to predict speed values and steering angles by taking previous feedback speeds and visual recordings as inputs. Experiments are conducted on the public Udacity dataset and a newly collected SAIC dataset. Results show that the proposed model predicts steering angles and speed values accurately. Furthermore, we improve the failure data synthesis methods to solve the problem of error accumulation in real road tests.**

I. Introduction

In many traditional self-driving car solutions [1], [2], [3], [4], [5], vehicle controls are rule based where perception and vehicle control are two individual modules. Nvidia [6] is the first to address the task of end-to-end steering angle control, where Convolutional Neural Networks (CNN) are used to regress steering angles directly from raw pixels recorded by front-view cameras. Xu et al. [7] further propose to predict the steering angle and understand the scene simultaneously in an end-to-end fashion with an FCN-LSTM architecture. A visual attention network [8] is proposed to help interpret the predictions with attention heatmaps. Other approaches [9], [10] are proposed to visualize the intermediate results in CNN.

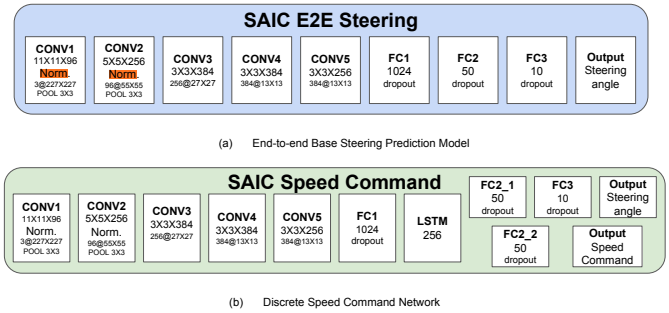
Despite the fact that the end-to-end steering angle control has achieved good results and has been well interpreted, the steering angle alone is not sufficient for vehicle control. The lack of speed commands greatly limits the potential applications of the end-to-end methods. In this work, we propose to predict the steering angle and speed command simultaneously with a multi-task learning approach. Intuitively, it is challenging to predict an accurate speed value with only visual inputs. A correct turning angle can be predicted with sufficient training data on the road, since there is only one correct way to keep the vehicle on the road. However, the driving speed is determined by a number of other factors including driver's driving habits, surrounding traffic conditions, road conditions and so on. Many factors cannot be reflected solely through front-view cameras. Therefore, we start with an easier task of discrete speed command prediction. The task is to predict discrete speed control commands of accelerating, decelerating and maintaining speed. The discrete speed control commands can be adequately inferred from front-view cameras. For example, a decelerating command is predicted when there are obstacles in the front, and an accelerating command may be predicted when the road is clear and the vehicle speed is low.

Although discrete speed commands provide a preliminary version of vehicle speed control, there exist two shortcomings. First, the levels of accelerating and decelerating are pre-fixed, which limit the smoothness [11] of the vehicle control. Second, using only the visual inputs limits the command prediction accuracy under certain circumstances. For example, when the vehicle is already fast enough or at the speed limit, the accelerating command should not be made even if the road is clear. In the initial model, the speed is inferred automatically from the input image sequences, and the prediction may be inaccurate. To achieve a better vehicle control, we propose to take previous feedback speeds as an extra modality, and predict speeds and steering angles simultaneously. The proposed model is evaluated on the public Udacity dataset [12] and the newly collected SAIC dataset. Experiment results show that the multi-modal multi-task network provides an accurate speed prediction while further improves the state-of-the-art steering angle prediction. Furthermore, we conduct real car tests on roads similar to the SAIC dataset's testing data. We also improve the failure case data synthesis methods to solve the problem of error accumulation.

Our main contributions include the following:

- We propose a multi-modal multi-task network for end-to-end steering angle and speed prediction.
- We collect a new SAIC dataset containing the driving records during the day and night. The dataset will be released upon the publication of this work.
- We improve the failure case data synthesis methods to solve the problem of error accumulation in real car tests.

[*] Both authors contributed equally to this work.



(a) End-to-end Base Steering Prediction Model

(b) Discrete Speed Command Network

Fig. 1. End-to-end steering and discrete speed command model.

II. Related Work

ALVINN [13] is one of the earliest successful neural network based self-driving vehicle project. The network is simple and shallow, but it manages to do well on simple roads with a few obstacles. With the development of deep learning [14], [15], many systems use CNN for environment perception and steering angle prediction. Nvidia is the first to adopt Convolutional Neural Networks (CNN) for end-to-end steering angle prediction [6]. They propose to predict steering angles with only three front-view cameras and manage to control the vehicle with the proposed system. There exist three main approaches: behavior reflex CNN, mediated perception and privileged training. Behavior reflex CNN [6], [8], [10], [16], [17], [18] directly predict the steering angle from the visual inputs. The system has a low model complexity and can be robust with enough training data. Furthermore, it has a good generalization ability. However, the performance is limited in complicated environments and the results are difficult to interpret. Some systems propose visualization methods [9], [10] and include attention mechanisms [8], [19], [20] to better interpret the results. Mediated perception [1] first maps visual inputs into several pre-defined parameters to depict the surroundings. Rule based methods then produce control commends with the estimated parameters. Such methods have a better vehicle control smoothness [11] but can only work in limited scenarios. Designing ideal control rules is also difficult. Privileged training [7], [21] is a multi-task approach that understands the scene and predicts vehicle commands simultaneously. The main limitation is the large amount of training data required. In this work, we expand the behavior reflex CNN with a multi-modal multi-task framework. Feedback speeds are used as an extra modality for steering angle and speed prediction.

III. Method

In this section, we first introduce the base CNN model for end-to-end steering angle prediction. Based on the improved CNN structure, a multi-task network is proposed to predict the steering angle and discrete speed command simultaneously by taking an image sequence as the input. Finally, we propose a multi-modal multi-task network that takes previous feedback speeds as an extra modality and predicts the speed and steering angle simultaneously.

A. Base Steering Model

It is shown in [6] that CNN has a good ability in extracting visual features and is capable of directly regressing the steering angle from raw pixels. Inspired by previous end-to-end steering angle prediction systems, we propose an improved CNN structure for this task with two improvements. As shown in Figure 1 (a), the model consists of 9 layers including 5 convolutional layers and 4 fully connected layers. Unlike previous work [6], the convolutional layers are designed based on AlexNet [15], [22] and a large kernel size is adopted in the first few layers. Experiments show that larger kernels are suitable for front-view cameras and can better capture the environment features. Another improvement is changing the aspect ratio of the input image to 1:1. Previous methods [6], [8] resize the input with a fixed aspect ratio of around 2.5:1. The convolutional kernels with a same width and height are then adopted. According to human intuitions though, visual content distributed along the y-axis is more informative for steering angle prediction. This implies that CNN kernels should have a larger width than height. For simplicity, we squeeze the input images in width to an aspect ratio of 1:1 and continue using the square kernels. Experiments show that the two improvements, the larger kernel size and reshaped aspect ratio, improve the performance of the end-to-end steering angle prediction. We further combine these two improvements with larger networks like VGG [23] and ResNet [24]. Although the model tends to overfit on all the evaluated datasets, the combination is promising in the future when larger datasets are available.

The mean absolute error is adopted as the training loss function. In addition, We apply different loss weights to alleviate the problem of data imbalance, as going straight appears more frequently than turning. The data with a small steering angle has a small training loss weight and the turning data has a larger weight. This technique is applied to all steering angle prediction models in this paper.

B. Discrete Speed Command Network

The end-to-end steering angle control successfully proves the feasibility of generating vehicle controls directly from front view cameras. However, the steering angle alone is not sufficient for vehicle control. The speed is another important parameter that needs to be predicted. Unlike the steering angle though, predicting the vehicle speed solely from a front view camera is counterintuitive, because even human drivers drive at different speeds given a similar road condition. Therefore, it is more reasonable to predict the speed control command from visual information, instead of directly predicting the desired speed values. For example, all drivers should slow down when the vehicle is too close to other cars or obstacles, and most drivers speed up when the road is clear. Based on this observation, we first propose a multi-task framework that predicts discrete speed commands and steering angles simultaneously. The model is called the speed command network.

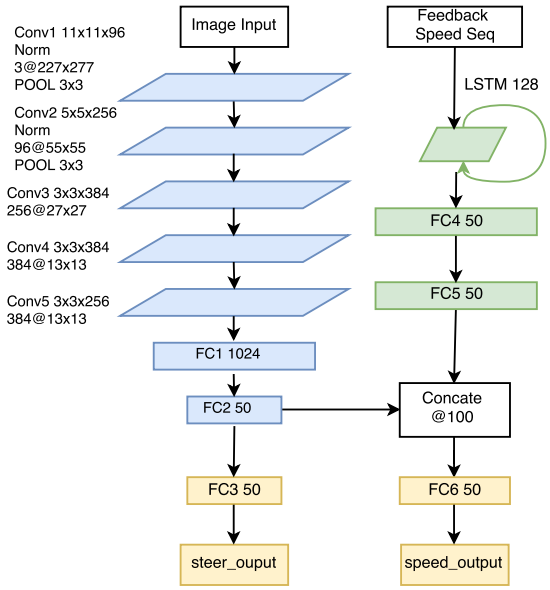


Fig. 2. End-to-end multi-modal multi-task vehicle control model. Different colors represent different modules.

As shown in Figure 1 (b), the speed command network takes an image sequence as the input and predicts discrete speed commands and steering angles simultaneously. The convolutional layers have a same structure as in the base steering model. The encoded visual features are fed into an LSTM layer for temporal analysis. The output image sequence feature is used for both steering angle regression and speed command classification. As a first step, the speed commands contain three classes: "accelerating", "decelerating" and "maintaining speed". The cross entropy loss is used for speed command classification and the mean absolute error is calculated for steering angle prediction. A weighting term is added as a hyper-parameter to adjust the importance of the two tasks.

C. Multi-modal Multi-task Network

The speed command network provides an initial framework for vehicle speed control. However, the performance is limited due to the lack of input information. The visual contents from the front view cameras alone are not sufficient for accurate speed command prediction. For example, in most cases it is reasonable to speed up when the road is clear, but it is not the case when the vehicle is already at a high speed. Similarly, there is no need to slow down when the vehicle is already slow enough. These failure cases are observed in the experiments and vehicle speeds are necessary for making a good speed command prediction. Theoretically, the vehicle speed can be predicted from image sequences, but the prediction is difficult and inaccurate. A more reasonable solution is to directly adopt the feedback speeds. Therefore, we propose a multi-modal multi-task network to predict the values of steering angles and speeds simultaneously by taking previous feedback speeds as an extra modality.

The model structure is shown in Figure 2. The network contains a visual encoder and a speed encoder. The visual encoder takes only one frame as inputs instead of using the CNN + LSTM structure. This greatly reduces the amount of computation, therefore guarantees a high FPS and a real-time performance even with low performance GPUs. The speed encoder encodes the pattern of previous feedback speed sequences. The encoded visual features are used for steering angle prediction, and the concatenation of visual features and feedback speed features are adopted for speed prediction. Both steering angle prediction and speed prediction apply mean absolute loss as a loss function, and a weighting parameter is tuned to adjust the weight between the two loss terms.

IV. Dataset

In this section, we first introduce the public Udacity dataset [12]. The collection and statistics of the SAIC dataset is then discussed. Example frames of both datasets are shown in Figure 3. Finally, we introduce the data pre-processing methods.

A. Dataset

1) Udacity: The Udacity dataset [12] is originally provided for an online challenge. The dataset contains six video clips with a total duration of around 20 minutes. Speed values, steering angles and video streams from three front view cameras are recorded.

2) SAIC: In order to obtain a larger data size and find regions for real road test, we record and build the SAIC dataset. The dataset includes five hours of driving data in north San Jose area, mostly on urban roads. The dataset contains the driving data in both day and night. The vehicle goes between several nodes and each trip between the nodes has a duration of around ten minutes. Parking, waiting at traffic lights and some other conditions are considered as noisy parts and filtered out. After filtering out the noisy videos, two hours' data is split into training, validation and testing set. A whole video of a certain trip between two nodes is atomic in set splits. Three drivers are included to avoid biasing towards a specific driving behavior. Similarly, video streams, speed values and steering angles are recorded. The video streams contain videos from one center and two side front view cameras with a frame rate of 30 frames per second.

B. Data Pre-Processing

1) Image Pre-Processing: We adopt several image pre-processing and data augmentation techniques to improve the robustness and prediction accuracy of the proposed system. The robustness under various lighting conditions is a major challenge for camera-based systems. We show that converting frames into different color spaces can improve the robustness towards lighting changes. The input frames are converted from RGB color space to HSV. A small rotation angle is randomly added to simulate the camera vibrations on vehicles. For data augmentation, random horizontal flips are first adopted. Another important technique is data synthesis with side cameras, which generates simulated failure cases for training.

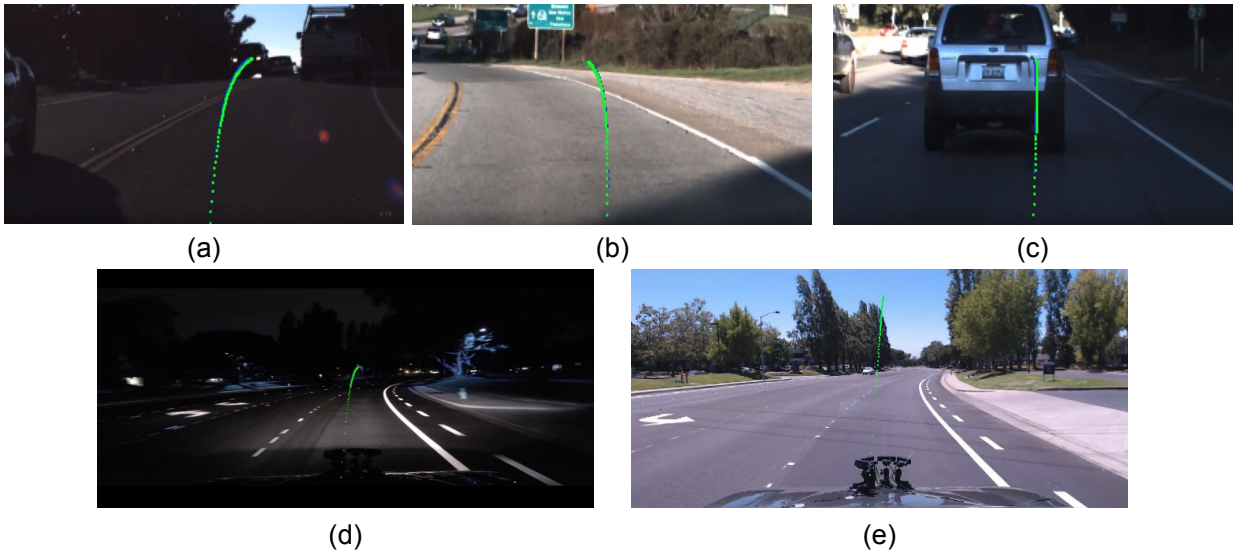


Fig. 3. Example frames and predictions on the Udacity and SAIC datasets. First row: the Udacity dataset. Second row: the SAIC dataset.

TABLE I
EXPERIMENT RESULTS OF STEERING ANGLE PREDICTION ON UDACITY

Method	Angle (MAE in $degree$)
Nvidia's PilotNet [6]	4.26
Cg Network [25]	4.18
Base Steering Model	2.84
Discrete Speed Command Network	1.85
Multi-modal Multi-task Network	1.26

2) Speed Command Generating: We introduce the methods for generating discrete speed commands. We first calculate acceleration from speed sequences with the following equation:

$$acce = \frac{speed_e - speed_s}{interval} \quad (1)$$

where $acce$ is the calculated acceleration, $speed_e$ is the speed at the end of the interval, $speed_s$ is the speed at the start of the interval. The $interval$ is set to one second in our experiment. Two acceleration thresholds are then selected to generate the labels for the three classes: "accelerating", "decelerating" and "maintaining speed". According to manual visual observations and domain experts' suggestions, 0.25m/s^2 and -0.25m/s^2 are selected as the upper and lower thresholds, respectively. The accelerations larger than 0.25m/s^2 are labeled as "Accelerating", and the values smaller than -0.25m/s^2 is tagged with "Decelerating". Remaining minor speed changes are labeled as "Maintaining Speed".

V. EXPERIMENT

The proposed method is evaluated on the public Udacity dataset [12] and the collected SAIC dataset. We first present the results of steering angle prediction. The performances of speed command predictions and speed value estimations are then evaluated. Finally, we introduce real car tests and an improved data synthesis method that solves the error accumulation problem in vehicle tests.

TABLE II
RESULTS OF SPEED VALUE PREDICTION ON THE UDACITY DATASET AND THE SAIC DATASET WITH MULTI-MODAL MULTI-TASK NETWORK

Dataset	Speed (MAE in m/s)
Udacity [12]	0.19
SAIC	0.45

A. Steering Angle Prediction

We first evaluate the performance of end-to-end steering angle prediction. The proposed multi-modal multi-task model is compared with several state-of-the-art models and the proposed improved single task network. Nvidia's PilotNet[6] and the Cg Network [25] proposed in the Udacity Self-Driving challenge is reimplemented and selected for comparison. As a regression task, the performance is reported in terms of MAE (Mean Absolute Error) in degree. Furthermore, we discard low speed data that is slower than $4m/s$. It is observed that steering angles tend to be much larger when vehicles are almost stopped, which are considered as noise in steerings.

The models are first evaluated on the Udacity dataset. As shown in Table I, the propose model is compared to the reimplemented Nvidia's PilotNet[6] and the Cg Network [25] from the Udacity Self-Driving challenge. Nvidia's PilotNet has five convolutional layers and five fully connected layers with an input of $200 * 66$. The Cg Network is even simpler with three convolutional layers and two fully connected layers. Furthermore, the proposed base steering model and the speed command network are compared in order to protrude the advantage of the proposed Multi-modal Multi-task network.

As shown in Table I, the improved base steering mode outperforms the reimplemented Nvidia's PilotNet[6] and the Cg Network [25]. This proves the effectiveness of the proposed CNN structure with larger kernel sizes and adjusted aspect ratios. PilotNet is proposed to work on other unpublished datasets, which might limit its performance in our evaluations.

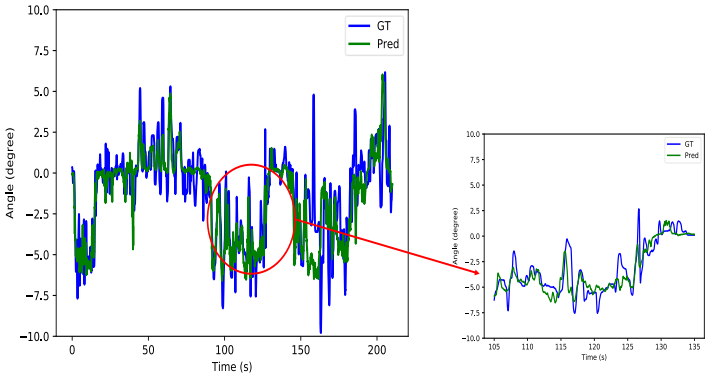


Fig. 4. Steering angle prediction results by the multi-modal multi-task network on the Udaicty dataset [12].

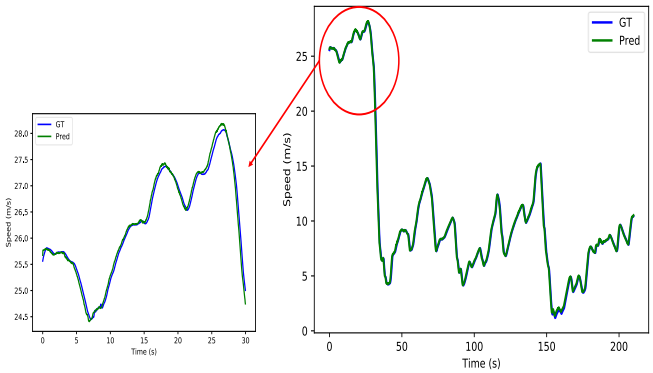


Fig. 5. Speed value prediction results by the multi-modal multi-task network on the Udaicty dataset [12].

By comparing the multi-task speed command model to the base steering model, we observe a further improvement in the steering accuracy from $2.84°$ to $1.85°$. This shows that the multi-task model provides additional speed prediction while further improves the performance of the steering angle prediction task. The multi-modal multi-task model further improves the steering accuracy from $1.85°$ to $1.26°$. As an extension, the multi-modal multi-task model takes previous feedback speeds as an extra modality of inputs and predict the speed and steering angle simultaneously. The extra modality and task help the model better understand the vehicle condition and thus generate a more accurate steering angle prediction.

Furthermore, we apply single exponential smoothing with thresholds [26], [8] on the final steering angle output. The intuition is to improve the vehicle control smoothness. The smoothing process adopts the following equation:

$$\hat{\theta}_t = \alpha * \theta_t + (1 - \alpha) * \hat{\theta}_{t-1} \tag{2}$$

where $\hat{\theta}_t$ is the smoothed steering angle output at the current frame, θ_t is the steering angle prediction at the current frame and $\hat{\theta}_{t-1}$ is the smoothed steering angle at the last timestamp. α is the smoothing factor and is set to 0.2.

Experiments are also conducted on the newly collected SAIC dataset. We achieve a steering angle prediction accuracy of $0.17°$ with the multi-modal multi-task network.

B. Discrete Speed Command Prediction

As introduced in Section III-B, we first simplify the speed prediction problem into a multi-class classification problem where the classes are discrete speed commands. Experiments are conducted on the Udacity dataset and the SAIC dataset with the model structure shown in Figure 1 (b). We convert acceleration value sequences into discrete speed command sequences containing the labels of 'accelerating', 'decelerating' and 'maintaining speed'. All discrete command labels are transferred into one-hot vectors.

On the Udacity dataset, we achieve a speed command classification accuracy of 65.0%. Furthermore, the multi-task model improves the steering angle prediction accuracy from $2.84°$ to $1.85°$. Despite the improvements in steering angle prediction, the results are limited. After observing the error classes, we find two major reasons for the failure cases. First, the generated speed commands are noisy with the human factors-related speed changes. Increasing the interval in calculating the acceleration can alleviate the problem, but it leads to a delay in generating the speed command. Another problem is that it is inherently difficult to predict the speed command with only the visual inputs. As mentioned earlier, there is no need to slow down when the vehicle is already slow enough even if the obstacles are close to the vehicle. To solve these problems, we further propose the multi-modal multi-task network.

C. Speed Control Value Prediction

The multi-modal multi-task network, shown in Figure 2, directly predicts the speed value of the next frame by utilizing both visual inputs and feedback speed inputs. Different from speed command prediction, the ground truth labels of speed values are numerical values in unit of m/s and the problem is now modeled as a regression task. For inputs, the visual input is one single frame and the feedback speeds contain the speeds of 10 previous timestamps. Similar to steering angle prediction, the low speed data (less than $4m/s$) is discarded to ensure a consistent driving condition. Experiments are conducted on both the Udacity and the SAIC datasets. The speed prediction performance of the multi-modal multi-task model is shown in Table II. We achieve an MAE of $0.19m/s$ on the Udacity dataset and an MAE of $0.45m/s$ on the SAIC dataset. Since the speed prediction task is novel, we did not find any baselines for comparison. The speed prediction results are plotted in Figure 5 and the predicted values match well with the ground truth. Furthermore, an improvement in steering angle prediction is observed with the multi-modal multi-task model.

D. Road Tests and Data Synthesis

Despite the good simulation results, we further discuss the challenges and corresponding solutions used in road tests. The major challenge in road tests is error accumulation. The accumulated error in the steering angle reflects as a shift vertical to the road and finally leads to the drift away of the vehicle. Similar error accumulation is also observed in speed control, as the feedback speeds have been used for future speed predictions. Therefore, the input data should contain adequate samples of recovering from failures. However, failure case data collection is dangerous and infeasible, since human drivers would have to frequently drive off the road and recover.

Inspired by [6], we use side cameras to synthesize the failure case data for steering angle prediction. An artificial recovering angle is added with the following equation:

$$\theta_f = \theta_r + \arctan(\frac{d_y}{s * t_r}) \quad (3)$$

where θ_f is the simulated steering angle with a recovering angle added, θ_r is the driver's steering angle corresponding to the center camera, d_y is the distance between the side and center cameras, s is the current speed and t_r is the time of the whole recovering process. In our experiments, the camera offset d_y is 20 inches (50.8 cm). Based on expert knowledge, we adopt a recovering time of one second in our experiments. Furthermore, we extend the data synthesis methods to speed data synthesis. Experiments on real cars show that vehicles would drift away without the data synthesis method. With the synthesized failure cases added, vehicles manage to drive autonomously on the road under a similar condition in SAIC.

VI. Conclusion

In this paper, we address the challenging task of end-to-end vehicle control in terms of both the speed and steering angle. A multi-modal multi-task framework is proposed for the joint task. The model takes front-view camera recordings and feedback speed sequences as the input. Experiments show that the proposed multi-task framework predicts the speed value accurately and further improves the accuracy of steering angle prediction. A new SAIC dataset is collected for evaluation and further studies. Finally, the error accumulation problem in real vehicle road tests are introduced. An extended data synthesis method is proposed for failure case simulation, which help solve the error accumulation problem.

Acknowledgments

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