A Personalized Highway Driving Assistance System

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A Personalized Highway Driving Assistance System *

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Abstract— **A control approach for automated highway driving is proposed in this study, which can learn from human driving data, and is applied to the longitudinal trajectory of an autonomous car. Naturalistic driving data are used as samples to train the model offline. Then, the model is used online to emulate what a human driver would do by computing acceleration. This reference acceleration is tracked by a predictive controller, which enforces a set of comfort and safety constraints before applying the final acceleration. The controller is designed to balance between maintaining vehicle safety and following the model's commands. Thus, the proposed controller can handle dynamic traffic situations while performing like a human driver. This approach is validated on two different scenarios using MATLAB simulations.**

I. INTRODUCTION

The field of autonomous driving has made significant progress over the last decades. Advanced driving assistance systems (ADAS) have been introduced and improved from simple cruise control and emergency braking systems to sophisticated partially or fully automated vehicles such as Google or Tesla self-driving cars.

The majority of the ADASs currently available are focused on safety, and they generate default maneuvers independent of the driver or passengers. However, different drivers have different driving styles and a pre-planned maneuver may not satisfy everyone. Thus, in this study it is proposed that drivers' styles be incorporated into the ADAS without compromising vehicle safety, in order to increase the drivers' satisfaction and comfort in autonomous vehicles. In this work, a highway driving assistance system is developed which performs according to the driver's preference. This system operates in three modes: path following, car following and lane change, which are the most common maneuvers in highway scenarios. The operation modes are chosen based on their compatibility with the driver's preference at the given traffic condition. The driver's preference is captured by analysis of each individual's driving data.

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The remainder of this paper is organized as follows. In section II the relevant work in the literature is discussed. In section III the driver modeling approach is described. The decision and control system is proposed in section IV, and simulation results are presented in section V. Finally, the conclusion and discussion are given in section VI.

II. RELATED WORK

While there are several studies on driver behavior modeling and autonomous driving, studies combining these subjects are less common in the literature. In this section the existing approaches are investigated in order to determine their advantages and disadvantages.

A. Personalized Driver Models

Driver models are developed for various purposes. One application of driver models is to define general frameworks for prediction of human drivers' actions in different scenarios. For example in [1] and [2], drivers' intentions of lane change and intersection crossing are predicted.

In other cases, driver models are integrated with controllers in order to replicate human drivers' styles in autonomous vehicles. A model for predicting drivers' steering input is developed in [3] using a compensatory transfer function and an anticipatory transfer function based on road geometry with parameters obtained from simulator experiments. In [4] and [5] lane change assistance systems are proposed. Relevance vector machine (RVM) is used in [4] to predict a driver's lane change intent in advance. In [5] a Gaussian mixture model (GMM) driver model is trained with real-world data, and it recommends a lane change maneuver. However, in both of these methods the system only offers suggestions and the driver performs the maneuver. In this case, the drivers may not follow the trajectory as well as expected and put themselves or other road users at risk.

The study on current personalized driving models reveals that there are several shortcomings to this type of driver modeling. The existing models simplify the behavior (e.g. constant speed assumption) or the environment (e.g. ignoring the traffic) which results in inaccurate and unrealistic models. Moreover, although the models are trained with real data, in most cases the data is used to optimize the model parameters. Therefore, the model may not perform well in an unseen scenario.

B. Maneuver Decision Making and Control

Lane changes have been one of the most investigated maneuvers in the literature, which is due to their frequency in

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both urban and highway driving, as well as their significant role in traffic accidents (73.5% of accidents [6]).

A survey in [7] has investigated lane change/merge control methods, in addition to some of the supporting tools including positioning, communication and simulation technologies. Lane change control can be categorized into two groups: decision making and trajectory planning. Trajectory planning has already been investigated extensively in the literature with approaches such as [8], [9] and [10]. Here, lane change decision studies are reviewed.

Optimal lane change decision controllers based on mixed integer programming (MIP) are proposed in [11] and [12]. In these approaches model predictive control is utilized to determine the required acceleration/deceleration as well as the optimal destination lane. However, formulating the problem with mixed logical dynamics could result in a non-convex problem, which MPC is not able to solve.

The lane change decision and trajectory controllers introduced here are either focused on maximizing vehicle safety or are based on drivers' data. Although vehicle safety is the most important factor, different driving preferences must also be considered in vehicle control.

III. Proposed Highway Driving Assistance System

The objective of the proposed system is to execute the highway driving maneuvers according to the driver's preferences while maintaining safety and road regulations. For this purpose, a driver model is integrated with the controller.

The model is developed according to an individual driver's driving data using Random Forest regression, and it generates a reference acceleration for the controller to follow. The controller utilized here is a model predictive control (MPC) system for tracking arbitrary references. MPC is chosen because of its low complexity and ability to handle state and input constraints over a horizon. The learning-based framework is adopted from [13] and extended to other highway maneuvers

The proposed system has three modes of operation, which are activated depending on the driver's preference and the surrounding environment condition. It should be noted that these modes can be overridden for a mandatory maneuver such as lane change for exit or merging. The main contributions of this study are a) developing a driver model using the random forest algorithm, b) employing an MPC controller for tracking dynamic references which will control the vehicle according to the driver's preference, and c) introducing a novel algorithm for alternating between different driving modes for maximum safety and comfort.

For simplicity, only the longitudinal motion control is investigated in this study. However, this approach can easily be extended to lateral motion as well. In this study, it is assumed that the subject vehicle is aware of its surrounding environment through correct and accurate vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communications, as well as the sensors and other equipment available to the vehicle.

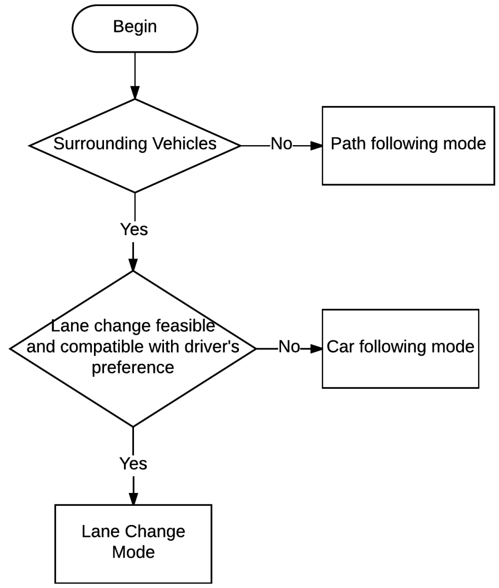

Fig. 1: Block diagram of the proposed algorithm

A. Decision Maker

This component decides which one of the three operation modes must be activated at each moment. The overall block diagram of the proposed algorithm is given in Fig. 1. The following conditions determine the operation mode:

I If there is no or very distant traffic, the system operates in the path following mode. The model predictive controller tracks the reference acceleration signal provided by the driver model as closely as possible.

II If there are other vehicles in the close vicinity of the subject vehicle, additional constraints are introduced to ensure the safety of the vehicle. As a result, the tracked acceleration may not be similar to its reference signal. In such cases, in order to follow the driver's preferences, the system explores the possibility of lane change. To accomplish this, multiple optimization problems are solved, one for remaining in the current lane and the others for moving to the adjacent lane(s). If moving to an adjacent lane results in lower cost, the system activates the lane change mode.

III If there are surrounding vehicles on the road and the lane change option is ruled out, the vehicle remains in its current lane. In this condition, the control system is more focused on vehicle safety by maintaining a safe gap between the front and rear vehicles.

B. Driver Model

Random forest regression model is used for modeling the driver's behavior. This model receives input data of the vehicle states and generates a reference acceleration for the controller to track. In this study, the input features are vehicle position and velocity. Before the actual training takes place, all the input variables are scaled so that their values remain in the range of $[0, 1]$ and the target variable (i.e. vehicle acceleration in x-axis) is transformed in exponential space.

Afterwards, the inputs are passed through a feature generator which produces features of the following form:

$$\mathcal{F} = [d \quad d^2 \quad d^3 \quad v \quad v*d \quad d^2*v \quad v^2 \quad d*v^2 \quad v^3] \quad (1)$$

where d and v represent vehicle position and velocity of the vehicle, respectively.

1) Random Forest Regression: Random Forest is an ensemble tree learning framework built upon bagging [15] method where many trees are grown based on bootstrap input samples.

C. Control System

In this part, the vehicle modeling and model predictive control employed in the study are presented.

1) Vehicle Dynamic Model: The longitudinal dynamic of the vehicle is modeled with a double integrator system, which is presented below:

$$d_{k+1} = d_k + v_k\delta t + a_k\frac{\delta t^2}{2} \quad k = 0, ..., N \tag{2a}$$

$$v_{k+1} = v_k + a_k\delta t \quad k = 0, ..., N \tag{2b}$$

where d_k, v_k, and a_k represent position, velocity and acceleration at time k, and δ_t represents the sampling time. The double integrator is used in this study for simplicity. However, the proposed highway driving assistance system can be implemented with more complex models.

2) MPC Controller: Due to the variations in the reference acceleration generated by the driver model, the controller must be able to follow the changes. Therefore, a novel model predictive controller for tracking periodic references is utilized in this study. This was first proposed in [16] and [17].

The cost function is defined as:

$$\begin{aligned} V_N(x, r_x, r_u; x^r, u^r, u_N) = V_t(x; x^r, u^r, u_N) \\ +V_p(r_x, r_u; x^r, u^r) \end{aligned} \tag{3}$$

where

$$V_p(r_x, r_u; x^r, u^r) = \sum_{i=0}^{T-1} \|x^r(i) - r(i)\|_S^2 + \|u^r(i) - r_u(i)\|_V^2 \tag{4}$$

and

$$V_t(x; x^r, u^r, u_N) = \sum_{i=0}^{N-1} \|x(i) - x^r(i)\|_Q^2 + \|u(i) - u^r(i)\|_R^2 \tag{5}$$

In this formulation, the parameters (x, r_x, r_u) are the state, the state reference and the input reference, and (x^r, u^r) are the planned reachable state and inputs respectively. In order for the cost function to be optimized, both terms are considered. The term $V_p(r_x, r_u; x^r, u^r)$ penalizes the deviation of the planned reachable trajectory from the desired reference signal over the period of T time steps. If the desired reference is unreachable, the controller's goal is to come up with an optimal reachable trajectory. The term $V_t(x; x^r, u^r, U_N)$ is the tracking error which defines the transient behavior of the controller. It minimizes the error between open loop trajectory and the planned reachable references over the prediction horizon N. In this study, for simplicity $N = T$.

Below, the MPC optimization problem for tracking a periodic reference signal is presented:

$$\min_{x^r, u^r, u_N} \quad V_N(x, r_x, r_u; x^r, u^r, u_N) \tag{6a}$$

$$x(0) = x_0 \tag{6b}$$

$$x(i+1) = Ax(i) + Bu(i) \quad i \in \mathbb{I}_{[0,N-1]} \tag{6c}$$

$$y(i) = Cx(i) + Du(i) \quad i \in \mathbb{I}_{[0,N-1]} \tag{6d}$$

$$(x(i), u(i)) \in \mathcal{Z} \quad i \in \mathbb{I}_{[0,N-1]} \tag{6e}$$

$$x^r(0) = x^r \tag{6f}$$

$$x^r(i+1) = Ax^r(i) + Bu^r(i) \quad i \in \mathbb{I}_{[0,T-1]} \tag{6g}$$

$$y^r(i) = Cx^r(i) + Du^r(i) \quad i \in \mathbb{I}_{[0,T-1]} \tag{6h}$$

$$(x^r(i), u^r(i)) \in \mathcal{Z}^c \quad i \in \mathbb{I}_{[0,N-1]} \tag{6i}$$

$$x(N) = x^r(N) \tag{6j}$$

This optimization problem will result in the solution (x^{r*}, u^{r*}, u_N^*), where $x_N^*(x, r)$ and $y_N^*(x, r)$ are the optimal predicted trajectories and $x_N^{r*}(x, r)$ and $y_N^{r*}(x, r)$ are the optimal planned trajectories for the states and outputs respectively.

In the above MPC problem, the predicted trajectory of the system from the current state is denoted by constraints (6b) to (6d) and the planned reachable trajectories from the initial state x^r are defined by constraints (6f) to (6h). The states and input constraints for predicted and planned reachable trajectories are given in constraints (6e) and (6i) respectively. Also, constraint (6j) ensures that the predicted trajectory reaches the planned reachable trajectory which guarantees closed loop convergence.

3) Optimization Constraints: Since the proposed system performs multiple maneuvers, different constraints are introduced for different scenarios based on the environment and the subject vehicle's condition.

Basic Constraints

The basic constraints are valid at any condition and are mainly related to road regulations and vehicle limitations. These limitations include:

- Velocity: The vehicle velocity should never be less than zero which is full stop, and should not exceed the road speed limit.

$$v_{min} \leq v_k \leq v_{max} \quad k = 0..N \tag{7}$$

- Acceleration: The acceleration range defined for the controller is determined from the vehicle's physical condition.

$$a_{min} \leq a_k \leq a_{max} \quad k = 0..N \tag{8}$$

- Acceleration Rate: In order to ensure the passengers' comfort, the the variations of acceleration (jerking) should remain in a small range.

$$\Delta a_{min} \leq \Delta a_k \leq \Delta a_{max} \quad k = 0..N \tag{9}$$

Car-following Constraints

If the vehicle will stay in its current lane, the constraints on the position only include maintaining a safety distance with the front and rear vehicles in the lane.

$$d_{max_k} = min(d_{front_i} - gap) \quad t = 0..N \tag{10a}$$

$$d_{min_k} = max(d_{rear_i} - gap) \quad t = 0..N \tag{10b}$$

Where d_{front} and d_{rear} denote the position of front and rear vehicles, and gap is the the minimum safety distance between subject vehicle and the surrounding vehicles.

If the surrounding vehicles are relatively close, a position reference signal is generated to fully utilize the gap by keeping the vehicle in the middle of the space between the vehicles (eq. 11).

$$d_{ref_k} = \frac{d_{min_k} + d_{max_k}}{2} \tag{11}$$

If a position reference is available, the weight distribution will change in favor of the position tracking, since safety has more priority than the driver's preference. The proposed weight distribution is given below:

$$R = \frac{1}{(N_v + 1)^2} \tag{12a}$$

$$Q = 1 - R \tag{12b}$$

Where N_v is the number of surrounding vehicles, R is the reference tracking weight in the cost function, and Q is the position tracking term in the cost function. Different weight distribution curves were considered, and the selected one gave satisfactory results. With this formulation, as the road gets more crowded, the driving assistance system will increase the priority of maintaining a safe distance with the surrounding vehicles.

Lane Change Mode Constraints

If the vehicle changes lane, the position constraints include the combined safety gap of both the current and target lanes. In the beginning of the lane change maneuver, while the vehicle is still in transition between lanes, the position constraints include the minimum and maximum safe positions mutual between current and target lanes.

$$d_{max_k} = min(d^{cl}_{front_i} - gap, d^{tl}_{front_i} - gap) \quad t = 0..t_{trans} \tag{13a}$$

$$d_{max_k} = min(d^{tl}_{front_i} - gap) \quad t = t_{trans}..N \tag{13b}$$

$$d_{min_k} = max(d^{cl}_{rear_i} - gap, d^{tl}_{rear_i} - gap) \quad t = 0..t_{trans} \tag{13c}$$

$$d_{max_k} = min(d^{tl}_{rear_i} - gap) \quad t = t_{trans}..N \tag{13d}$$

where, t_{trans} is the duration of time that the vehicle requires to move from one lane to the other, and d^{cl} and d^{tl} denote the position in current lane and target lane respectively.

IV. Simulation and Results

In this section, performance of the system is evaluated. First the driver model estimation accuracy is tested, and then the behavior of the proposed highway assistance system is examined in different scenarios. Simulation of MPC controller is done with CVXGEN convex optimization solver [18] in MATLAB.

TABLE I: Scenario vehicles' parameters

	Current Lane	Adjacent Lane
Scenario 1	Subject: $[d, v] = [0, 25]$ No surrounding vehicles	No vehicles
Scenario 2	Subject: $[d, v] = [0, 26]$ V1: $[d_{v1}, v_{v1}] = [-15, 22]$ V2: $[d_{v2}, v_{v2}] = [16, 28]$	V3: $[d_{v3}, v_{v3}] = [-20, 28]$

TABLE II: Design parameters for the longitudinal control

$v_x \in \{0, 35\}[m/s^2]$	$\Delta a_x \in \{-0.5, 0.5\}$	$N = 15$
$a_x \in \{-2, 2\}[m/s]$	$gap = 5[m]$	$\delta t = 0.4$

A. Driver Model

1) Naturalistic Driving Data: The dataset used for training and testing the driver model is the 2nd Strategic Highway Research Program (SHRP 2) data samples [19].

2) Model Training: Due to the large quantity of missing data, imputation is used to increase the number of observations. Since acceleration is the target variable, no imputation is done for these missing values and corresponding observations are discarded from further use. Next, all available values of acceleration are used to create a model for the position. In this stage of the experiment, a random forest model is used with 500 trees using 10 fold cross validation, repeated 3 times. This is put in place to avoid overfitting in the training phase. Once the random forest model is trained, it is used to predict the missing values of position. In the subsequent stage of imputation, these newly imputed values for position and acceleration are used to predict the missing values of velocity following the same procedure described above. As a result of this imputation process, the number of observations increased from 397 to 4231.

Once the feature generation is done, 75% of available observations are used for training while the remaining 25% are used for testing purposes. The training samples are used to train a random forest model with 10-fold cross-validation, and a different number of random variables sample are tried in order to achieve the best possible training. Once the training is complete, the trained model is used to predict the vehicle acceleration of test samples and transformed back to original scale using a natural log transformation. Fig. 2 and 3 demonstrate the performance of the trained model on test (i.e. out-of-bag (OOB)) samples.

B. Driving Scenarios

The performance of the proposed approach is evaluated in two different traffic scenarios. In Scenario 1, there are no vehicles in the vicinity of the subject vehicle, which is considered as the subject vehicle being alone on the road (Figure 4). In Scenario 2, the subject vehicle is surrounded by three other vehicles. The vehicles $V1$ and $V2$ are moving in the same lane at the front and back of the subject vehicle, and $V3$ is moving in the adjacent lane as shown in Figure 5. The scenario vehicles parameters and controller design parameters are given in Tables I and II respectively.

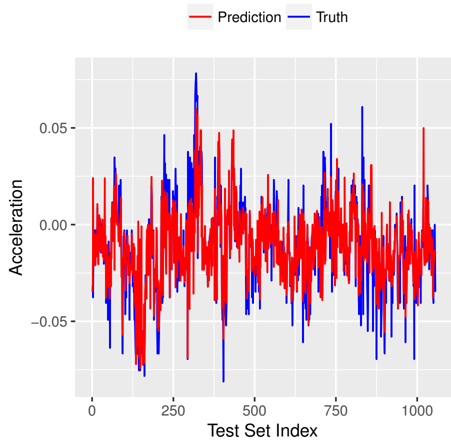

Fig. 2: Raw acceleration predictions using the trained model from one randomly chosen validation step in 10-fold CV, tested on OOB samples

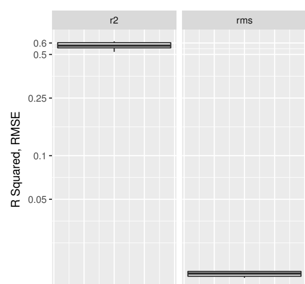

Fig. 3: Performance of model as tested on OOB samples in 10-fold CV from 10 iterations. Very low RMSE indicates good prediction on OOB samples and R-squared value greater than 0.55 indicates good explaining ability.

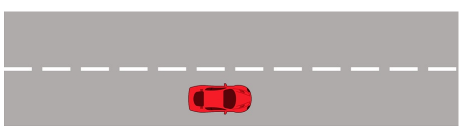

Fig. 4: Illustration of scenario 1

The simulation results for scenario 1 are given in Fig. 6. It shows that the controller is tracking the driver model's output with very small error. This accurate tracking is due to the absence of surrounding vehicles which led to the reference acceleration tracking being the single control objective. As a result, the lane change decision maker does not make a command for moving to the adjacent lane and the vehicle remains in its current lane.

In simulation of scenario 2, the presence of $V1, V2$ and $V3$ close to the subject vehicle results in more conservative position constraints for maintaining vehicle safety, which leads to poor tracking of acceleration compared to scenario 1. In the current lane, a position reference is generated to keep the vehicle at a safe distance from both front and rear vehicles. The addition of position reference leads to a new distribution of weights in the controller cost function. As previously mentioned, the importance of position tracking term in the controller increases with the number of surrounding vehicles. As a result, the controller focuses more on tracking the reference position rather than tracking the reference acceleration, which is what happened in Fig. 7. In addition, it is observed that in the beginning of the car following mode the vehicle decelerates to increase its distance with $V2$, but after a while the distance is increased due to $V2$'s high velocity, so the subject accelerates again to maintain its position in the middle and avoid a collision with $V1$.

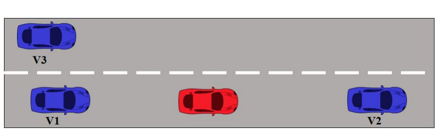

Fig. 5: Illustration of scenario 2

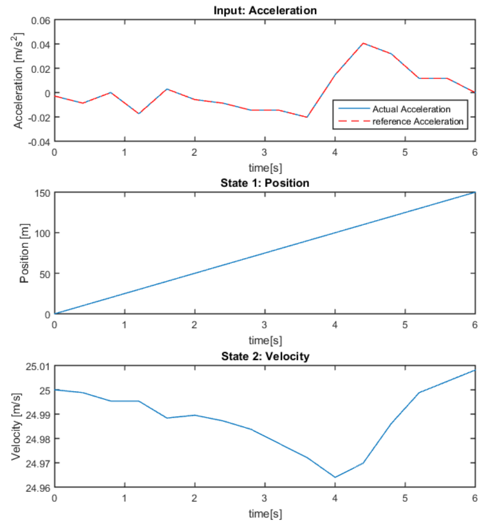

Fig. 6: Planned trajectory for subject vehicle in scenario 1

TABLE III: RMSE for different vehicle trajectories in scenario 2

	Root Mean Squared Error
Current Lane	4.8613
Target Lane	6.089×10^{-11}

Since the controller is not performing according to the driver's preference, the controller considers moving to the next lane. In the adjacent lane, there is only a minimum position constraint is defined, which means more weight is on the acceleration tracking term again. The results are shown in Fig. 8. It can be seen that the acceleration is tracked more accurately. The RMSE of acceleration tracking for the two modes is given in Table III. Therefore, the vehicle goes into the lane change mode in order to be able to perform according to the driver's preference.

V. Conclusion and Future Work

In this study a highway driving assistance system is presented which performs according to the driver's preference. This system consists of a data driven driver model integrated with a model predictive controller, and operates in three modes: path following, car following and lane change. The driver model is trained using naturalistic driving data and can emulate different driving styles. The MPC ensures safety by enforcing a set of constraints on the vehicle state. The

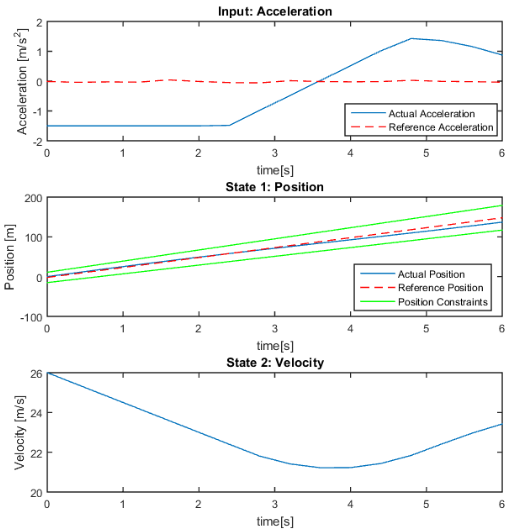

Fig. 7: Planned trajectory for subject vehicle in scenario 2 (in current lane)

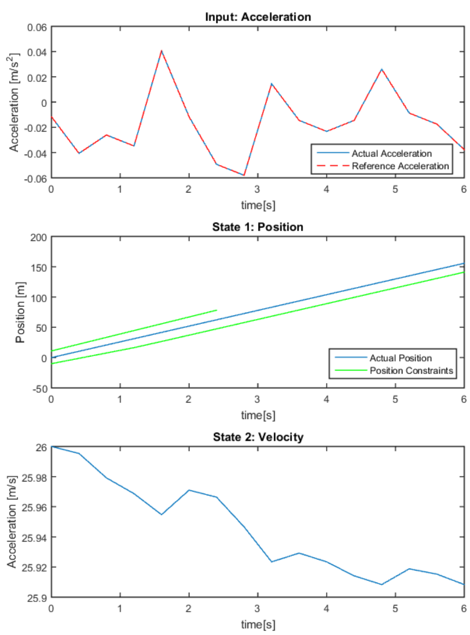

Fig. 8: Planned trajectory for subject vehicle in scenario 2 (in target lane)

system can detect and handle driving situations where vehicle safety is the priority specifically in the presence of multiple surrounding vehicles. In addition, the system is able to make a lane change decision if it will satisfy the drivers' preference. The proposed method is simulated for the longitudinal control of an autonomous car in two different scenarios. The results demonstrated that the proposed approach is able to handle both light and congested traffic situations. These results demonstrate that the proposed approach performs well on the task it was designed for, that is, to learn from driving data and emulate driving styles while ensuring safety.

In the future, the driver model will be extended to include different driving models and be able to detect and adapt to a new driver's style as soon as possible. Also, an additional filtering component will be added to ensure that a lane change is compatible with the driver's preference given a different environmental conditions. Moreover, considering the proposed system's dependency on V2X communications, an approach should be developed to ensure maneuver safety in case of receiving incorrect or inaccurate information about the surrounding traffic.

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