

Lateral Control for Automated Vehicle Following System in Urban Environments

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ABSTRACT

In contrast to highway, there are some sections not well maintained in urban roads. In these sections, there may be faint lane marks or static obstacles due to construction or some other reasons. Therefore, an automated vehicle following system such as traffic jam assistant should consider these sections to guarantee the safety of the system. In order to achieve this purpose, a model predictive control (MPC) scheme has been developed. The objectives of MPC are to compute the sequence of optimal steering input for vehicle following with obstacle avoidance. For this, the MPC uses the lead vehicle's state and obstacle's position obtained by lidars. For this purpose, a simplified nonlinear model of the vehicle was used to predict the future evolution of the system. Based on this prediction, performance index is optimized under operating constraints at each time step. A test vehicle equipped with two lidars on left and right corner of the front bumper has been developed. And the performance of the proposed MPC-based steering control algorithm has been investigated via vehicle test. Test results show the robust performance of vehicle following in urban environments.

CITATION: Kim, D. and Kim, H., "Lateral Control for Automated Vehicle Following System in Urban Environments," *SAE Int. J. Trans. Safety* 2(2):2014, doi:10.4271/2014-01-0161.

1. INTRODUCTION

The increase in the number of vehicles on the road results in a progressive saturation of the road network. So many drivers in the big city are suffered from traffic congestion. In addition to the immediate impacts on drivers (wasting time, stress, aggressiveness), congestion of the road network also has significant economic and environmental costs. In order to solve this problem, some car manufactures and car-part makers are developing a system that helps driver in the monotonous situation. This kind of system typically uses radar and camera technology to keep pace with other vehicles and provide automatic steering control to stay in the current lane.

In order to perform these functions, this system usually consisted of two parts: longitudinal control and lateral control. The longitudinal control have been studied for almost half a century and many challenges associated with it have been resolved[1][2]. However, there are many problems yet to be solved for lateral control of vehicle following system.

Approaches used to solve the perception problem could be classified into three categories[3]: GPS[4][5], active sensors[6][7][8] and passive sensor[9][10][11]. In GPS based approach, the positions of the leader vehicle are echoed to the follower vehicle to generate and adjust of the follower's path. The main advantage is that no perception sensors are needed and the system can be operated day and night. However, its reliability depends on the availability of GPS data. For example in built

areas or where dense tree foliage covers satellite signals, its confidence is very low since availability of GPS cannot be guaranteed. Active sensor(Lidar) based approach is the most stable in various road condition, however, the tracked target may escape from the single line scan sensor's field of view(FOV) when the vehicle travels on an irregular terrain. In passive sensor(Vision) based approach, the sensor can provide more information about the environment, nevertheless, the orientation of the leader vehicle can cause errors on the tracking algorithms. And Environmental conditions such as lighting pose are severe constraints in this approach.

Approaches used to control the lateral motion of vehicle could be classified into two categories: direct control and trajectory based control. Direct control approaches[12][13] are very similar to path tracking. They formulate inter-vehicle kinematics in error coordinate and design the steering controller using adaptive control theory. In trajectory based approaches[14][15], that use the time history of the lead vehicle, i.e., the ego-vehicle has to follow the path of the leader. Robustness and real-time performance of these methods have been validated. However, the disadvantage of methods is that the system cannot respond to obstacles excepting lead vehicle.

In this paper, we proposed the new method to guarantee the safety of automated vehicle following system in urban environments. In order to achieve this, model predictive control(MPC) has been applied to control the lateral motion of

vehicle. An optimal following problem while avoiding collision with obstacles is formulated in terms of cost minimization under constraints. Information on obstacles is incorporated online in the nonlinear model-predictive framework as they are sensed within a limited sensing range. The overall problem is solved online with nonlinear programming. And, in order to build such system, we use single line scan sensor that is one of the most robust sensor in various road condition. To solve the problem of FOV mentioned above, extended Kalman filter has been applied to our system.

2. CONTROL ARCHITECTURE

The proposed vehicle following system consists of a vehicle tracking part and a vehicle following part, as shown in [figure 1](#).

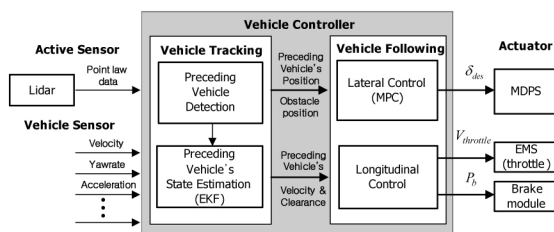


Figure 1. Control structure

Tracking algorithm is designed to detect the lead vehicle from point clouds of two lidars (shown in [figure 2](#)) based on the geometrical configuration and to estimate its states using extended Kalman filter. In a vehicle following part, lateral controller determines the optimal steering input using model predictive control method and longitudinal controller determines the throttle/brake inputs for keeping pace with lead vehicle.



Figure 2. Lidar sensor configuration

3. VEHICLE TRACKING

A vehicle tracking algorithm consists of two parts: a vehicle detection and a state estimation. The detection algorithm extracts the information about relative position and heading angle of lead vehicle from point clouds. And the state estimation algorithm estimates velocity, yawrate as well as the information obtained by prior process. Furthermore, the estimator provides area where lead vehicle is expected to exist at the next time step for vehicle detection.

3.1 Vehicle Detection

To detect a lead vehicle, point clouds acquired from two lidars mounted on each side of the front bumper were segmented based on distance between the two points adjacent. And then, vehicle detection algorithm classifies the segment that corresponds to the lead vehicle. For this, expected location of lead vehicles calculated by tracking algorithm is used as shown in [figure 3](#). Next we extract information about relative position and heading angle from the segment obtained by prior process using Ramer algorithm [16]. Ramer algorithm is an algorithm for reducing the number of points in a curve that is approximated by a series of points. The purpose of the algorithm is, given a curve composed of line segments, to find a similar curve with fewer points. In this paper, Ramer algorithm is used to model a set of points by one or two segments as shown in [Fig. 4](#).

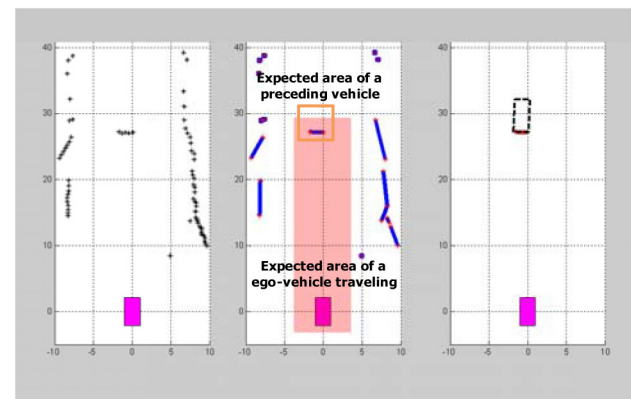


Figure 3. Processing flow at each scan

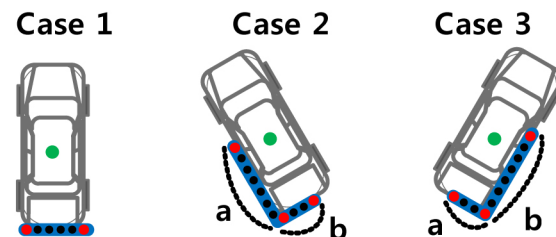


Figure 4. Position estimation from point clouds

Finally, vehicle detection algorithm calculates the position of vehicle center and heading angle depending on the case presented in the figure above.

3.2 Vehicle Tracking

The extended Kalman filter is used to estimate lead vehicle states such as longitudinal velocity, yaw rate, longitudinal acceleration and yaw acceleration from lead vehicle's relative position obtained through prior process and the vehicle sensor signals such as longitudinal velocity yaw rate under the assumption of the Gaussian white noise [17]. The state vector x is defined as following in order to represent lead vehicle's planar behavior:

$$x = [p_{x,rel} \quad p_{y,rel} \quad \theta_{rel} \quad v \quad \gamma_{rel} \quad \gamma_{acc} \quad \gamma_{jerk}]^T$$

where $P_{x,rel}$, $P_{y,rel}$, θ_{rel} is the lead vehicle's position relative to ego-vehicle, V_{pre} , γ_{pre} , a_{pre} , $\dot{\gamma}_{pre}$ is its longitudinal velocity, yaw rate, longitudinal acceleration and yaw acceleration. The measurement vector is defined as follows.

$$z = \begin{bmatrix} p_{x,rel} & p_{y,rel} & \theta_{rel} \end{bmatrix}^T \quad (2)$$

Assuming that the time derivatives of lead vehicle's longitudinal acceleration and the yaw acceleration can be considered to be the process noise, the process model and measurement model are given as follows:

$$\begin{aligned} x_{k+1} &= f(x_k, u_k) + w_k \\ z_k &= h(x_k) + v_k \end{aligned} \quad (3)$$

where

$$f(x) = x + \begin{bmatrix} v \cos \theta_{rel} - v + p_{y,rel} \cdot \gamma \\ v \sin \theta_{rel} - p_{x,rel} \cdot \gamma \\ \gamma_{pre} - \gamma \\ a_{pre} \\ \dot{\gamma}_{pre} \\ 0 \\ 0 \end{bmatrix} \cdot \Delta t, \quad h(x) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

where Δt is the sampling time which set to be 0.1 second in this study, v , γ is ego-vehicle's longitudinal velocity and yawrate. The process noise is assumed to be a white noise with associated covariance matrix, W . The measurement noise is also assumed to be a white noise with associated covariance, V . With above process and measurement model, lead vehicle states are recursively estimated by using the extended Kalman filter which is a sequence of time and measurement update steps as following specific equations:

Time update

$$\begin{aligned} \bar{x}[k] &= f(\hat{x}[k-1]) \\ F[k-1] &= \left. \frac{\partial f}{\partial x} \right|_{x=\hat{x}[k-1]}, \quad H[k-1] = \left. \frac{\partial h}{\partial x} \right|_{x=\hat{x}[k-1]} \\ M[k] &= F[k-1] \cdot P[k-1] \cdot F[k-1]^T + W \end{aligned}$$

Measurement update

$$\begin{aligned} \hat{x}[k] &= \bar{x}[k] + K[k] \cdot (z[k] - H \cdot \bar{x}[k]) \\ K[k] &= M[k] H^T \cdot (H M[k] H^T + V[k])^{-1} \\ P[k] &= (I - K[k] H) \cdot M[k] \end{aligned}$$

Abnormal measurements are often occurred due to the pitch motion of ego vehicle or the slope of the road. In the case as shown in the right two graphs of figure 5, vehicle detection algorithm can't extract information about lead vehicle. However, it is possible to predict the lead vehicle's state only using time update process because these symptoms occur for a while. So we estimate the lead vehicle's state only using time update process during which the abnormal measurements are occurred.

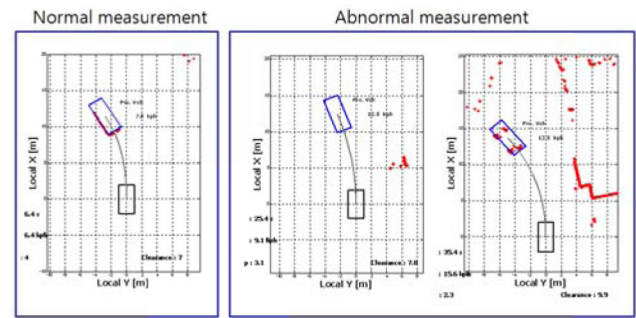


Figure 5. Vehicle tracking using extended kalman filter

4. VEHICLE TRACKING

4.1 Lateral Control

In order to use MPC for lateral control, it is necessary to construct a vehicle model for the path generation. In the vehicle model, the state is defined by including the longitudinal velocity, heading angle, the derivative of heading angle and longitudinal/lateral position of a vehicle, as given in equation (4). With this definition, the state equation is obtained as follows:

$$\dot{\xi} = \begin{bmatrix} \beta & \psi & \dot{\psi} & X & Y \end{bmatrix} \quad (4)$$

The state equation can be written using validated parameters from the previous section as given in equation (5).

$$\frac{d}{dt} \begin{bmatrix} \beta \\ \psi \\ \dot{\psi} \\ X \\ Y \end{bmatrix} = \begin{bmatrix} \frac{-2(C_f + C_r)}{mv_x} \beta + \left(\frac{-2(l_f C_f - l_r C_r)}{mv_x^2} - 1 \right) \dot{\psi} + \frac{2C_f}{mv_x} \delta_f \\ \dot{\psi} \\ \frac{-2(l_f C_f - l_r C_r)}{I_z} \beta + \frac{-2(l_f^2 C_f + l_r^2 C_r)}{I_z v_x} \dot{\psi} + \frac{2l_f C_f}{I_z} \delta_f \\ v_x \cos \psi - v_x \tan \beta \sin \psi \\ v_x \sin \psi + v_x \tan \beta \cos \psi \end{bmatrix} \quad (5)$$

The control input (u) is the steering angle (δ_f), and the output is set to be the position of the vehicle in the inertial reference frame. Therefore, the trajectories can be generated based on the output variables as follows: