

Adaptive Cruise Control with Collision Avoidance in Multi-Vehicle Traffic Situations

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ABSTRACT

This paper presents a longitudinal control algorithm for an adaptive cruise control (ACC) with collision avoidance (CA) in multiple vehicle traffic situations. The proposed algorithm consists of a multi-target tracking filter, a primary target selection algorithm and an integrated ACC/CA system. The multi-target tracking filter is used to smooth the sensor signal, and makes it possible to apply to a control system. The primary target selection algorithm decides an in-lane target and provides the information to an integrated ACC/CA system in order to drive a subject vehicle smoothly and improve safety in complex traffic situations. Finally, the integrated ACC/CA system computes the desired acceleration. The performance and safety benefits of the multi-vehicle ACC/CA system is investigated via simulations using real data on driving. Simulation results show that the response of multi-vehicle ACC/CA system is more smooth and safer at a change of traffic situations.

INTRODUCTION

Adaptive Cruise Control (ACC) is a common and well known automotive driver assistance system. By relying on a frontal radar or a lidar sensor, it can automatically adjust speed in order to maintain a safe headway distance between vehicles in the same lane. These systems use a simple scheme which declares the target

vehicle as the closest one currently in subject's lane. Major drawbacks resulting from this basic approach are the inability to detect vehicle on other lane and perform adequate reactions in advance and the limited performance in high curvature environments. Current research and development aim at establishing a future ACC system that predicts expected traffic situation and performs adequate reactions [5].

In order to create such an application, it is necessary for the ACC system to take into account the traffic in the front of the subject vehicle. In addition, sensors and processing systems should be used, that can detect and represent the complete traffic scene ahead of the vehicles. Up to now, several researchers have focused on the target tracking problem. Taking a view on a whole classical detection and tracking system architecture, consisting of a detection stage, a data association stage, a succeeding tracking module and a final track validation, the primary task of the tracking stage is to filter the measured state variables, hence to reduce the sensor measurement noise, and to estimate temporal derivatives of state variables over time. Besides the state uncertainty, which is treated in a Bayes-optimal way by recursive Bayesian state estimation like it is implemented with Conventional Kalman, Extended Kalman, Unscented Kalman and Particle Filters [1,9]. To achieve good data association and tracking behavior in the presence of noise, probabilistic data association filters with gating techniques are used [4]. Since most of the time a neighboring vehicle's motion can be

described well, multiple model filters are used in the estimation process [2,3]. As illustrated above, there are many researches about detecting and tracking vehicle target based on single or multiple sensors. However, it is important to not only detect and track the multiple vehicles, but also establish a control strategy using the tracking results in order to apply to multiple-vehicle traffic scenes. Specifically speaking, it is necessary to determine whether the neighboring vehicle is in driver's lane and calculate a control input considered cutting into subject's lane. Some work still need to be done about a control algorithm applied to multiple vehicle traffic scenes. Rainer Möbus proposed an algorithm for solving a multi-object adaptive cruise control problem. The problem is solved via hybrid system theory [1]. In a multi-object traffic scene the optimal acceleration is to be found respecting traffic rules, safety distances and driver intentions.

This paper proposes a longitudinal control algorithm for adaptive cruise control with collision avoidance in multiple vehicle traffic situations. In this study, a multi-target tracking logic based on a kalman filter and a primary target selection algorithm has been presented, and the ACC/CA controller is provided by our previous research [7,10]. The overall performance of the multi-vehicle ACC/CA system has been investigated via simulations using experimental data collected from test vehicle in real road.

MULTI -TARGET TRACKING FILATER

Generally speaking, a multi-target tracking filter is used to group all of the detected objects from sensor into distinct targets according to similar attributes. State estimation techniques are used to smooth the measured data and improve accuracy. The structure of the multi-target tracking algorithm outlined in this paper is shown in Fig. 1.

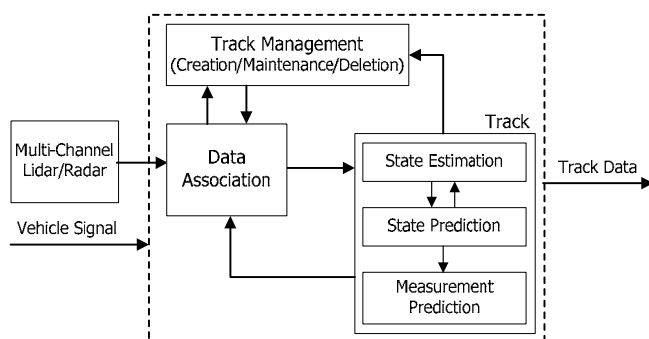


Fig.1 Scheme of a multi-target tracking filter

DYNAMIC AND MEASUREMENT MODEL - Various algorithms are needed to process collected sensor data. Therefore, it is necessary to introduce the following model of relative longitudinal and lateral dynamics of the subject vehicle and the neighboring vehicle. Let the state

vector at discrete-time k consist of position and velocity components of the target in the Cartesian coordinates.

$$x(k) = \begin{bmatrix} p_x & p_y & v_x & v_y \end{bmatrix}^T \quad (1)$$

where p_x is the relative longitudinal position, v_x is the relative longitudinal velocity, p_y is the relative lateral position and v_y is the relative lateral velocity. The discrete-time kinematic model for neighboring vehicle are described by

$$x(k+1) = \Phi x(k) + \Gamma w(k) \quad w(k) \sim N(0, Q) \quad (2)$$

$$\Phi = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \Gamma = \begin{bmatrix} T^2/2 & 0 \\ 0 & T^2/2 \\ T & 0 \\ 0 & T \end{bmatrix} \quad Q = \begin{bmatrix} \sigma_{long}^2 & 0 \\ 0 & \sigma_{lat}^2 \end{bmatrix}$$

where T is the sampling time, taken as 0.05(sec) in this study. The process noise, $w(k)$, is white noise assumed to be Gaussian distributed with zero mean and known covariance, $Q(k)$. The discrete-time measurement model is used to reflect the available sensor information arriving from a radar and a lidar.

$$z(k) = Hx(k) + v(k) \quad v(k) \sim N(0, R) \quad (3)$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad R = \begin{bmatrix} \sigma_x^2 & \sigma_{xy}^2 \\ \sigma_{xy}^2 & \sigma_y^2 \end{bmatrix}$$

where $v(k)$ is also a white, Gaussian noise with zero mean and associated covariance $R(k)$. The measurement arriving from a radar or a lidar are in polar coordinates and converted accordingly to Cartesian coordinates.

$$z(k) = \begin{bmatrix} z_1 & z_2 \end{bmatrix}^T \quad (4)$$

$$z_1 = r \cdot \cos \theta \quad z_2 = r \cdot \sin \theta$$

where r and θ are the range and azimuth measurements, respectively. The measurement errors, which are specified as standard deviation in polar coordinates by the sensor, namely σ_r and σ_θ , can be converted to Cartesian coordinates using the following form shown in [8].

DATA ASSOCIATION – The data association is necessary to decide whether tracks from different channels actually represent the same target. To achieve good data association and tracking behavior in the presence of noise, probabilistic data association filters with gating techniques are mainly used [4,8].

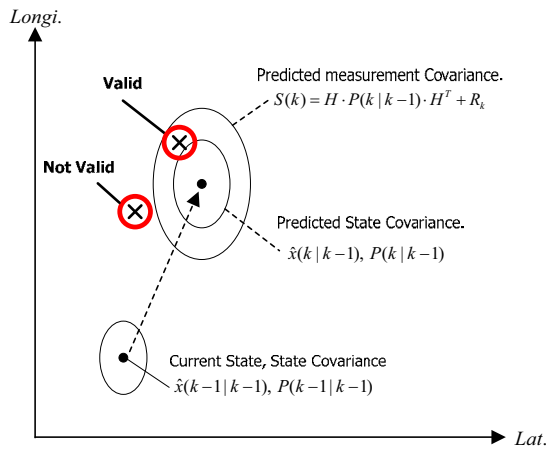


Fig.2 Scheme of Data Association

In the previous step for every tracking target, an updated representation with regard to the current time is generated. These estimated states are the basis for the following step, which predicts what each sensor would measure under the assumption that every tracking target was correctly estimated. The next step is the data association that extracts and assigns corresponding pairs of real and predicted measurements. Corresponding residual vector $r(k)$ is given by

$$r(k) = z(k) - H \cdot x(k|k-1) \quad (5)$$

The residual covariance matrix $S(k)$ is determined by

$$S(k) = H \cdot P(k|k-1) \cdot H^T + R(k) \quad (6)$$

with $H(k)$ describing the observation matrix and $R(k)$ the measurement noise. A measurement is declared valid if the normalized residual fulfills the following threshold condition.

$$\sqrt{r(k)^T S(k)^{-1} r(k)} \leq c \quad (7)$$

Statistically more than 99% of all measurements lie within the gate defined by choosing c as shown in Fig. 2. The probabilistic data association approach uses all measurements that are valid according to this gating. All valid measurements are used to update in a kalman filter

TRACK MANAGEMENT - As shown in Fig 3, several processes are required during each time step to handle the creation of new tracks when a target enters the field of sensor view, as well as to delete tracks when targets leave [6]. In this study, there are two kinds of tracks which are the preliminary and maintenance stages. The preliminary track is only used to confirm that a newly arriving target is a significant target. The maintenance track is those tracks assigned to established targets, to which measurements are associated and state estimates are updated through the use of a kalman filter.

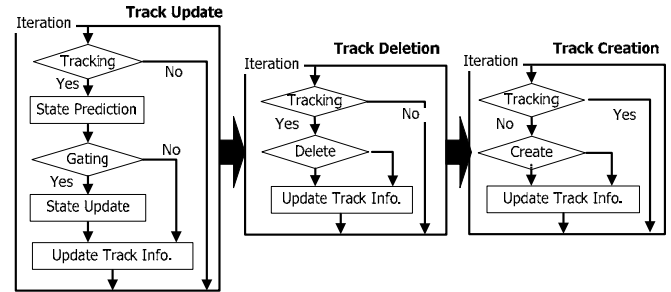


Fig.3 Flow of a track management

This includes the time it takes to initialize a new track, verify that at least two consecutive measurements are returned from the target and promote it to preliminary track. If the update counter of preliminary track exceeds a certain threshold, it is considered valid and then promoted to an established maintenance track. If targets move out of a range of the sensors or a maintenance track received no association, the time-prediction process is performed as the current estimate and increases its missed measurement counter. If the missed measurement counter of a track exceeds a certain threshold, it is deleted.

PRIMARY TARGET SELECTION

The information concerning estimated targets from the multi-target tracking logic cannot be fed directly to the ACC/CA system because it is only able to follow one preceding vehicle. Thus it is necessary to determine which neighboring vehicle is the primary vehicle to be followed. In this study, a primary vehicle is defined as the important target which has an effect on the subject vehicle among the neighboring vehicles. Figure 4 shows a scheme of the primary target selection algorithm introduced here to incorporate additional information available from the multi-target tracking logic. The proposed primary target selection algorithm consists of a yaw-rate based subject vehicle's lane detection, a motion based analysis, and an integration process. In our primary target selection algorithm, there are two assumptions: one is that the subject vehicle is in the center of the lane and the other is that the lane width is known.

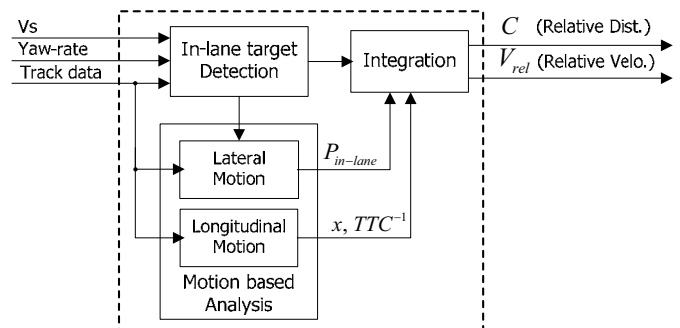


Fig.4 Scheme of a primary target selection