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Dynamic estimation of headway distance in vehicle platoon system under unexpected car-following situations

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Abstract

The headway distance between vehicles in a platoon is difficult to measure unless the vehicles are equipped with costly equipment such as laser or radar sensors, or an image processing system. This paper proposes an alternate approach to estimating headway distance indirectly from measurable variables such as the acceleration rate and velocity of selected vehicles in the platoon. Assuming a six-vehicle platoon, a particle filter (PF) and an unscented Kalman filter (UKF) are applied in order to estimate the headway of each vehicle based on the measurement variables of three (or all) vehicles in the platoon. The state-space models of the PF and the UKF are given by the conservation equation of headway and the conventional car-following model. To evaluate the PF and UKF performance, two scenarios were prepared: one assumed that prior knowledge of a model parameter differed from what was actually observed as posterior information, the other was a situation where a platoon vehicle slowed down unexpectedly during the car-following process. In both situations, the state-space model itself was unable to describe the dynamics of headway distance precisely, and the PF and the UKF were applied to minimize the headway distance errors caused by the incorrect model parameter and the unexpected vehicle slowdown. Numerical analysis demonstrated that both the PF and UKF were successful in estimating the headway distance, even when the car-following model did not express the true car-following phenomena. We also determined that, if all vehicles are equipped as probe cars, and thus capable of measuring the acceleration rate and velocity, the PF is superior to UKF when estimating the headway distance precisely. However, UKF is more stable than the PF when measurements are not taken from all vehicles, especially when a vehicle in the platoon unexpectedly slows downs during the car-following process.

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1. Introduction

The headway distance of longitudinal car-following vehicles is the most important parameter when evaluating the risk of front-to-rear-end collisions [Takada et al.(2012); Marumo et al.(2013)]. The automatic collision avoidance systems that have been developed by many vehicle manufactures to date "directly" measure the headway distance between vehicles using on-board distance measurement sensors. However, such sensors are too expensive to be installed on all of the vehicles in a platoon. Therefore, instead of the direct measurements, estimating or calculating the headway distance "indirectly" from measurable variables is a preferable technique.

In previous studies, the authors have applied particle filters (PFs), unscented Kalman filters (UKFs), and extended Kalman filters (EKFs) to the problem of dynamic headway distance estimations in a platoon system [Suzuki and Nakatuji (2013); Suzuki (2013)]. The PF and UKF are especially well known as powerful tools, and have been widely applied to various dynamic estimation problems including traffic state estimations [Pueboobpaphan et al., 2007], estimation of an origin-destination matrix [Pueboobpaphan and Nakatsuji (2011)], estimating visual shape and motion [Blake et al., 2001], mobile robot control [Fox et al., 2001], target tracking [McGinnity and Irwin (2001)], among others. Our previous study also showed that they are superior to other conventional estimation methods, including EKF, in estimating the headway distance of each vehicle in a platoon.

In this study, the state-space model of feedback estimators is defined by the conservation equation of headway and the conventional car-following model. The conservation equation is used as the state equation of the state-space model, whereas the car-following model is used for the measurement equation.

As explained above, the PF and the UKF perform extremely well in estimating the headway distance of platooned vehicles if the measurement equation calculates the acceleration rate precisely [Suzuki and Nakatsuji (2013)]. However, in an actual platoon situation, the state-space model is not always able to describe actual car-following behavior. In other words, the real acceleration and deceleration behavior of human drivers are not always equal to the calculation outputs provided by the theoretical car-following model. This is especially true when a vehicle in the platoon slows down unexpectedly. In such situations, the headway distance behavior is significantly different from the results computed by the theoretical model. Therefore, even in situations where the model does not precisely describe actual car-following behavior, headway estimations should be as accurate as possible in order to provide sufficient levels of precision.

In the present research, we prepared different car-following model parameter sets for use when generating observation data, beginning with the assumption that the prior information on model parameters would be different from actual posterior observations. Additionally, it is assumed that a vehicle in a platoon would slow down unexpectedly during the car-following process. We then evaluated the performance of the PF and the UKF by determining how capable they were of minimizing errors caused by the model parameter deviation and the unexpected vehicle slowdown.

2. Theoretical background

2.1. State-space model

The following state and measurement equations are defined as the state-space model:

$$\mathbf{x}_k = \mathbf{f}\left(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}\right) + \mathbf{v}_{k-1}, \tag{1}$$

$$\mathbf{y}_k = \mathbf{g}\left(\mathbf{x}_k\right) + \mathbf{w}_k, \tag{2}$$