A Nonlinear Information Filter for Tracking Maneuvering Vehicles in an Adaptive Cruise Control Environment

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Abstract: In this paper, a nonlinear information filter (IF) for curvilinear motions in an interacting multiple model (IMM) algorithm to track a maneuvering vehicle on a road is investigated. Driving patterns of vehicles on a road are modeled as stochastic hybrid systems. In order to track the maneuvering vehicles, two kinematic models are derived: A constant velocity model for linear motions and a constant-speed turn model for curvilinear motions. For the constant-speed turn model, a nonlinear IF is used in place of the extended Kalman filter in nonlinear systems. The suggested algorithm reduces the root mean squares error for linear motions and rapidly detects possible turning motions.

Keywords: Hybrid estimation, interacting multiple model, nonlinear filtering, extended Kalman filter, information filter, adaptive cruise control, constant-speed turn model.

1. INTRODUCTION

Recently, the majority of automobile companies are developing various driver assistance systems to increase vehicle safety and alleviate driver workload. The driver assistance systems include adaptive cruise control (ACC), lane-keeping support, collision warning and collision avoidance, and assisted lane changes. The effectiveness of these driver assistant systems depends on the interpretation of the information arriving from sensors, which provide details of the surrounding vehicle environment and of the driver-assisted vehicle itself. In particular, all these systems rely on the detection and subsequent tracking of objects around the vehicle. Such detection information is provided by radar, lidar, and vision sensor. The assistance systems mentioned above have certain objectives that their controllers try to meet. Before a controller can make a decision that enables the driver feel natural, the motion of the surrounding objects must be properly interpreted from the available sensor information [3].

Fig. 1 shows the configuration of an ACC system. The ACC system consists of a driver interface, a radar sensor which measures both the distance and speed of preceding vehicles, a controller which controls both throttle and brake actuators, and actuators [14, 20]. The ability to accurately predict the motion of preceding vehicles in the ACC environment can improve the controller's ability to adapt smoothly to the behavior of those vehicles preceding it. This ability to predict motions is dependent on how well the radar of an ACC vehicle can track other vehicles. In order to track other vehicles using the object information obtained from multiple sensors, tracking techniques based on the Bayesian approach are usually used [2]. The tracking of a maneuvering target is already well-established topic in the target tracking literature.

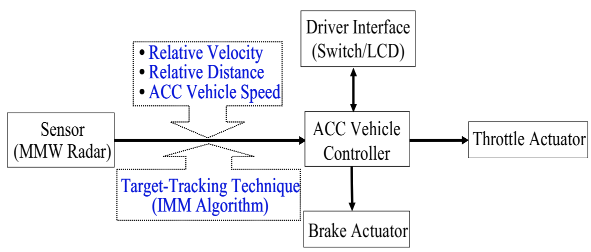

Fig. 1 Configuration of an ACC system

Techniques for tracking maneuvering targets are used in many tracking and surveillance systems as well as in applications where reliability is the main concern [2, 8, 11, 15, 16]. In particular, tracking a maneuvering target using multiple models can provide better performance than using a single model. A number of multiple model techniques to track a maneuvering target have been proposed in the literature: the multiple-model algorithms [15], the interacting multiple model (IMM) algorithm [2, 16, 18, 28], the adaptive IMM [6, 7, 12, 21], the fuzzy IMM [4, 19], the adaptive Kalman filter (KF) [7], and others.

Generally, target motion models can be divided into two subcategories: the uniform motion model and the maneuvering model. A maneuvering target moving at a constant turn-rate and speed is usually modeled as a maneuvering model, and called a coordinated turn model [2, 5, 6, 10, 12, 16, 21]. For application to air traffic control, a fixed structure IMM algorithm with a single constant velocity model and two coordinated turn models was analyzed [16]. And, for the tracking of a maneuvering target, a validation method of a new type of flight mode was presented in [24]. Nabaa and Bishop [24] validated a non-constant speed coordinated turn aircraft maneuver model by comparing their model with the classic Singer maneuver model and a constant-speed coordinated turn model using actual trajectories. Semerdjiev and Mihaylova [27] discussed variable- and fixed-structure augmented IMM algorithms, whereas a fixed-structure algorithm only was discussed in [16], and applied to a maneuvering ship tracking problem by augmenting the turn rate error.

As an alternative method to improve the track fusion, the information filter (IF) [1, 2, 17, 22, 23], which is claimed algebraic-equivalent to the KF [1], was developed. The IF is essentially a KF expressed in terms of measures of information about state estimates and their associated covariances. That is, the IF algorithm is a KF expressed in terms of information-analytic variables, which are measures of the amount of information about the parameter (state) of interest. This filter has been called the inverse covariance form of the KF [22].

Despite its potential application, however, it was not widely used and it was thinly covered in the literature. Bar-Shalom [2] and Maybeck [17] briefly discussed the idea of information estimation, but they did not explicitly derive the algorithm in terms of information as done by Mutambara [22], nor did they use it as a principal filtering method. In this paper, a nonlinear IF [9, 22, 23, 25], replacing the EKF, is used for the curvilinear model. The algorithm itself uses the same IMM logic, but the model-matched EKF is replaced by the model-matched nonlinear IF. The objective of this paper is to design a nonlinear IF for curvilinear motions in an IMM algorithm to track a maneuvering vehicle for the driving of an ACC vehicle on a road.

The contributions of this paper are as follows. First, the IMM algorithm is provided as a driving algorithm for an ACC vehicle in driving on a road. Second, two kinematic models for the possible driving patterns of vehicles are derived: A constant velocity model for linear motions and a constant-speed turn model for curvilinear motions are discussed. Third, for the constant-speed turn model, a nonlinear IF is used in place of the EKF. Fourth, the suggested algorithm reduces the root mean squares error in the case of rectilinear motions and detects the occurrence of maneuvering quickly in the case of turning motions.

This paper is organized as follows: In Section 2, we provide the various driving patterns of vehicles. A stochastic hybrid system is formulated, and two kinematic models are discussed. In Section 3, we compare a nonlinear IF with an EKF for a constant-speed turn model in an IMM algorithm. In Section 4, we evaluate the performance of these filters using Monte Carlo simulation under the various driving patterns. Section 5 concludes the paper.

2. PROBLEM FORMULATION

In this section, after analyzing the driving patterns of a vehicle on a road, a stochastic hybrid system in the form of an IMM algorithm for tracking the preceding vehicle using sensors (radar, lidar, sonar, vision, etc) is formulated. Also, two kinematic models representing the analyzed driving patterns are introduced.

2.1 Driving patterns

Fig. 2 depicts the various driving patterns of a vehicle: straight line and curve, cut-in/out, u-turn, and interchange. All of these patterns can be represented by a combination of a constant-velocity rectilinear motion, a constant-acceleration rectilinear motion, a constant angular velocity curvilinear motion, and a constant angular acceleration curvilinear motion. As kinematic models for describing these motions, two stochastic models will be investigated: one for rectilinear motion and the other for curvilinear motion. These typical driving patterns are described briefly as follows:

i) Straight line and curve: In this situation, the ACC vehicle tracks a preceding vehicle that follows straight lines and curves on a curved road [13, 26].

ii) Cut-in/out: The cut-in/out indicates the situation in which a maneuvering vehicle cuts in (or out) to (or from) the lane while the ACC vehicle is tracking other vehicle. In this situation, the tracking of up to three surrounding vehicles is assumed: one in front, one to the left, and one to the right. In this case, the target vehicle changes its motion from a rectilinear motion to a curvilinear motion and then back to a rectilinear motion.

iii) U-turn: This situation occurs when the target vehicle changes its driving direction by $180°$. The u-turn consists of three routes as follows: The target vehicle moves rectilinearly, undergoes a uniform circular turning of up to $180°$ with a constant yaw rate, and then converts to a rectilinear motion in the opposite direction.

iv) Interchange: When the ACC vehicle is passing through an interchange, the target vehicle undergoes a 3-dimensional motion. The target vehicle moves rectilinearly, undergoes a uniform circular turning of up to $270°$ with a constant yaw rate, and then converts to a rectilinear motion. In this paper, passing an interchange will be simplified by a 2-dimensional motion.

It will be shown in the sequel that a constant-velocity model will capture both constant velocity and acceleration rectilinear motions without and with an additional noise term, respectively. On the other hand, a constant-speed turn model will cover both constant angular velocity and angular acceleration curvilinear motions without and with a noise term, respectively.

2.2 Stochastic hybrid system

Following the work of Li and Bar-shalom [16], a stochastic hybrid system with additive noise is considered as follows:

$$x(k) = f[k-1, x(k-1), m(k)] + g[k-1, x(k-1), \nu[k-1, m(k)], m(k)] \tag{1}$$

with noisy measurements

$$z(k) = h[k, x(k), m(k)] + w[k, m(k)] \tag{2}$$

where $x(k) \in \Re^{n_x}$ is the state vector including the position, velocity, and yaw rate of the vehicle at discrete time k, $m(k)$ is the scalar-valued modal state (driving mode index) at instant k, which is a homogeneous Markov chain with probabilities of transition given by

$$P\{m_j(k+1) \mid m_i(k)\} = \pi_{ij}, \quad \forall m_i, m_j \in \mathrm{M} \tag{3}$$

where $P\{\cdot\}$ denotes the probability and M is the set of modal states, that is, constant velocity, constant acceleration, constant angular rate turning with a constant radius of curvature, etc. The considered system is hybrid since the discrete event $m(k)$ appears in the system. In the driving of ACC vehicle, $m(k)$ denotes the driving mode of the preceding vehicle, in effect during the sampling period ending at k, that is, the time period $(t_{k-1}, t_k]$. The event for which a mode m_j is in effect at time k is denoted as

$$m_j(k) \overset{\Delta}{=} \{m(k) = m_j\} \tag{4}$$

$z(k) \in \Re^{n_z}$ is the vector-valued noisy measurement from the sensor at time k, which is mode-dependent. $\nu[k-1, m(k)] \in \Re^{n_\nu}$ is the mode-dependent process noise sequence with mean $\bar{\nu}[k-1, m(k)]$ and covariance $Q[k\text{-}1, m(k)]$. $w[k, m(k)] \in \Re^{n_z}$ is the mode-dependent measurement noise sequence with mean $\overline{w}[k, m(k)]$ and covariance $R[k, m(k)]$. Finally f, g, and h are nonlinear vector-valued functions.

2.3 Two kinematic models

The concept of using noise-driven kinematic models comes from the fact that noises with different levels of variance can represent different motions. A model with high variance noise can capture maneuvering motions, while a model with low variance noise represents uniform motions. The multiple-models approach assumes that a model can immediately capture the complex system behavior better than others.

Two kinematic models for rectilinear and curvilinear motions are now derived. First, assuming that accelerations in the steady state are quite small (abrupt motions like a sudden stop or a collision are not covered), linear accelerations or decelerations can be reasonably well covered by process noises with the constant velocity model. That is, the constant velocity model plus a zero-mean noise with an appropriate covariance representing the magnitude of acceleration can handle uniform motions on the road. In discrete-time, the constant velocity model with noise is given by

$$x(k)=\begin{bmatrix}1 & T & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & T\\ 0 & 0 & 0 & 1\end{bmatrix}x(k-1)+\begin{bmatrix}\frac{1}{2}T^2 & 0\\ T & 0\\ 0 & \frac{1}{2}T^2\\ 0 & T\end{bmatrix}v(k-1) \quad (5)$$

where T is the sampling time (i.e., 0.01 sec in this paper), $x(k)$ is the state vector including the position and velocity of the preceding vehicle in the longitudinal (ξ) and lateral (η) directions at discrete time k, that is,

$$x(k)=[\xi(k)\ \dot{\xi}(k)\ \eta(k)\ \dot{\eta}(k)]' \quad (6)$$

with ξ and η denoting the orthogonal coordinates of the horizontal plane; and v is a zero-mean Gaussian white noise representing the accelerations with an appropriate covariance Q. If $v(k)$ is the acceleration increment during the k th sampling period, the velocity during this period is calculated by $v(k)T$, and the position is altered by $v(k)T^2/2$.

Second, a discrete-time model for turning is derived from a continuous-time model for the coordinated turn motion [2, p. 183]. A constant speed turn is a turn with a constant yaw rate along a road of constant radius of curvature. However, the curvatures of actual roads are not constant. Hence, a fairly small noise is added to a constant-speed turn model for the purpose of capturing the variation of the road curvature. The noise in the model represents the modeling error, such as the presence of angular acceleration and non-constant radius of curvature. For a vehicle turning with a constant angular rate and moving with constant speed (the magnitude of the velocity vector is constant), the kinematic equations in the (ξ,η) plane are

$$\ddot{\xi}(t)=-\omega\dot{\eta}(t),\quad \ddot{\eta}(t)=\omega\dot{\xi}(t) \quad (7)$$

where $\ddot{\xi}(t)$ is the normal (longitudinal) acceleration and $\ddot{\eta}(t)$ denotes the tangential acceleration, and ω is the constant yaw rate (ω > 0 implies a counterclockwise turn). The tangential component of the acceleration is equal to the rate of change of the speed, that is, $\ddot{\eta}(t)=d\dot{\eta}(t)/dt=d(\omega\xi(t))/dt$, and the normal component is defined as the square of the speed in the tangential direction divided by the radius of the curvature of the path, that is, $\ddot{\xi}(t)=-\dot{\eta}^2(t)/\xi(t)=-\omega^2\xi^2(t)/\xi(t)$ where $\dot{\eta}(t)=\omega\xi(t)$. The state space representation of Eq. (7) with the state vector defined by $x(t)=[\xi(t)\ \dot{\xi}(t)\ \eta(t)\ \dot{\eta}(t)]'$ becomes

$$\dot{x}(t)=Ax(t) \quad (8)$$

where

$$A=\begin{bmatrix}0 & 1 & 0 & 0\\ 0 & 0 & 0 & -\omega\\ 0 & 0 & 0 & 1\\ 0 & \omega & 0 & 0\end{bmatrix}.$$

The state transient matrix of the system, Eq. (8) is given by

$$e^{At}=\begin{bmatrix}1 & \frac{\sin\omega t}{\omega} & 0 & -\frac{1-\cos\omega t}{\omega}\\ 0 & \cos\omega t & 0 & -\sin\omega t\\ 0 & \frac{1-\cos\omega t}{\omega} & 1 & \frac{\sin\omega t}{\omega}\\ 0 & \sin\omega t & 0 & \cos\omega t\end{bmatrix}. \quad (9)$$

It has been remarked that if the angular rate ω in Eq. (7) is time-varying, Eq. (9) would be no longer true. In the sequel, following the approach in [2, p. 466], a "nearly" constant-speed turn model in a discrete-time domain is introduced. In this approach, the model itself is motivated from Eq. (9), but the angular rate is allowed to vary.

A new state vector by augmenting the angular rate $\omega(k)$ to the state vector of Eq. (7) is defined as follows:

$$x^a(k)=[\xi(k)\quad \dot{\xi}(k)\quad \eta(k)\quad \dot{\eta}(k)\quad \omega(k)]' \quad (10)$$

where superscript a denotes the augmented value. Then, the nearly constant-speed turn model is defined as follows [2, p. 467]:

$$x^a(k)=\begin{bmatrix}1 & \frac{\sin\omega(k-1)T}{\omega(k-1)} & 0 & -\frac{1-\cos\omega(k-1)T}{\omega(k-1)} & 0\\ 0 & \cos\omega(k-1)T & 0 & -\sin\omega(k-1)T & 0\\ 0 & \frac{1-\cos\omega(k-1)T}{\omega(k-1)} & 1 & \frac{\sin\omega(k-1)T}{\omega(k-1)} & 0\\ 0 & \sin\omega(k-1)T & 0 & \cos\omega(k-1)T & 0\\ 0 & 0 & 0 & 0 & 1\end{bmatrix}x^a(k-1)$$

$$+\begin{bmatrix}\frac{T^2}{2} & 0 & 0\\ T & 0 & 0\\ 0 & \frac{T^2}{2} & 0\\ 0 & T & 0\\ 0 & 0 & T\end{bmatrix}v^a(k-1). \quad (11)$$

Evidently, both Eq. (5) and Eq. (11) are special forms of Eq. (1). In addition, it is reasonable to assume that the transition between the driving modes of an ACC vehicle has the Markovian probability governed by Eq. (3). Consequently, the kinematic behaviors of an ACC vehicle can be suitably described in the framework of the stochastic hybrid systems.

3. A NONLINEAR IF IN AN IMM ALGORITHM

3.1 The linear IF

In order to accurately track the motion of preceding vehicles in the ACC environment, an IMM algorithm is used in this paper. The concept (structure) of the IMM algorithm during one cycle is given in [2, p.454] and [16]. In this paper two models of the IMM algorithm are used: one for rectilinear motion and the other for curvilinear motion. The tracking procedure of the vehicle in a rectilinear motion using Eq. (5) is carried out by the standard Kalman filter, which is not discussed in this paper.

The IF is essentially a KF expressed in terms of measures of information about the parameters (states) of interest rather than direct state estimates and their associated covariances [22, 23]. This filter has also been called the inverse covariance form of the KF [1]. We will review the information filtering equations for a comparison with the KF equations.

Denote the information matrix as $Y(k\,|\,k)\overset{\Delta}{=}P^{-1}(k\,|\,k)$ and information state as $\hat{y}(k|k)\overset{\Delta}{=}P^{-1}(k|k)\hat{x}(k|k)$, respectively. Then, the main IF equations are given as

i) Time update (prediction)

$$\hat{y}(k\,|\,k-1)=L(k\,|\,k-1)\hat{y}(k-1\,|\,k-1),$$

$$Y(k\,|\,k-1)=[F(k-1)Y^{-1}(k-1\,|\,k-1)F'(k-1)+Q(k-1)]^{-1}, \quad (12)$$

ii) Measurement update

$$\hat{y}(k\,|\,k)=\hat{y}(k\,|\,k-1)+H'(k)R^{-1}(k)z(k),$$

$$Y(k\,|\,k)=Y(k\,|\,k-1)+H'(k)R^{-1}(k)H(k) \quad (13)$$

where the information prediction coefficient $L(k\,|\,k-1)$ is given by

$$L(k|k-1) = Y(k|k-1)F(k-1)Y^{-1}(k-1|k-1) . \quad (14)$$

Remark 1: For the linear system and measurement equations, the KF provides a recursive solution for the estimate $\hat{x}(k|k)$ of the state $x(k)$ in terms of the estimate $\hat{x}(k|k-1)$ and the new observation $z(k)$. However, it is preferable to employ an IF since in multi-sensor structures the IF is easier to employ than the KF [1]. The IF is a more direct and natural method of dealing with multi-sensor data fusion problems than the conventional covariance-based KF. The attractive features of the IF are as follows: First, there are no gain or innovation covariance matrices and the maximum dimension of a matrix to be inverted is the state dimension. In multi-sensor systems the state dimension is generally smaller than the observation dimension, hence it is preferable to employ the IF and invert smaller information matrices than use the KF and invert larger innovation covariance matrices. Second, initializing the IF is much easier than for the KF. This is because information estimates (matrix and state) are easily initialized to zero information. Third, the IF is easier to distribute and fuse than the KF. However, for tracking curvilinear motions, which requires the estimation of ω with a new augmented model Eq. (8) in Section 2, a nonlinear IF is used.

3.2 The nonlinear IF

Since the model in Eq. (11) is nonlinear, the estimation of the state Eq. (10) will be performed via the nonlinear IF. This filter is equivalent to the EKF and linearizes the nonlinear model around the predicted state to obtain the best linearized estimates for the nonlinear system. The nearly constant-speed turn model of Eq. (11) can be rewritten as follows:

$$x^a(k) = f^a[x^a(k-1), \omega(k-1)] + G(k-1)\nu^a(k-1) \quad (15)$$

where the function $f^a(\cdot)$ is known and remains unchanged during the estimation procedure. The noise transition matrix $G(k\text{-}1)$ is the same form as that given in Eq. (11). Then, the nonlinear IF equations are given as

i) Time update (prediction)

$$\hat{y}(k|k-1) = Y(k|k-1)f^a[k, \hat{x}^a(k-1|k-1), \omega(k-1)]$$
$$Y(k|k-1) = [f^a_{x^a}(k)Y^{-1}(k-1|k-1)f'^a_{x^a}(k) + Q^a(k)]^{-1} \quad (16)$$

ii) Measurement update

$$\hat{y}(k|k) = \hat{y}(k|k-1) + h'^a_{x^a}(k)R^{-1}(k)[\upsilon(k) + h^a_{x^a}(k)\hat{x}^a(k|k-1)]$$
$$Y(k|k) = Y(k|k-1) + h'^a_{x^a}(k)R^{-1}(k)h^a_{x^a}(k) \quad (17)$$

where

$$f^a_{x^a}(k-1) = [\nabla_{x^a} f^a(x^a, \omega)']'|_{x^a = \hat{x}^a(k-1|k-1)}$$

$$= \begin{bmatrix} 1 & \frac{\sin\hat{\omega}(k-1)T}{\hat{\omega}(k-1)} & 0 & -\frac{1-\cos\hat{\omega}(k-1)T}{\hat{\omega}(k-1)} & f_{\omega,1}(k-1) \\ 0 & \cos\hat{\omega}(k-1)T & 0 & -\sin\hat{\omega}(k-1)T & f_{\omega,2}(k-1) \\ 0 & \frac{1-\cos\hat{\omega}(k-1)T}{\hat{\omega}(k-1)} & 1 & \frac{\sin\hat{\omega}(k-1)T}{\hat{\omega}(k-1)} & f_{\omega,3}(k-1) \\ 0 & \sin\hat{\omega}(k-1)T & 0 & \cos\hat{\omega}(k-1)T & f_{\omega,4}(k-1) \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

is the Jacobian of the vector f^a evaluated at the latest estimate of the state, Q^a is the covariance of the process noise in Eq. (15), $h^a_{x^a}(k) = [\nabla_{x^a} h^a(x^a, \omega)']'|_{x^a = \hat{x}^a(k|k-1)}$ is the Jacobian of the vector h^a evaluated at the predicted state $\hat{x}^a(k|k-1)$, and $\upsilon(k)$ is the innovation given by $\upsilon(k) = z(k) - h^a(k, \hat{x}(k|k-1), w(k))$. The partial derivatives with respect to ω in Eq. (18) are given by

$$f_{\omega,1} = \frac{T\hat{\dot{\xi}}(k-1|k-1)\cos\hat{\omega}(k-1)T}{\hat{\omega}(k-1)} - \frac{\hat{\dot{\xi}}(k-1|k-1)\sin\hat{\omega}(k-1)T}{\hat{\omega}(k-1)^2} - \frac{T\hat{\dot{\eta}}(k-1|k-1)\sin\hat{\omega}(k-1)T}{\hat{\omega}(k-1)} - \frac{\hat{\dot{\eta}}(k-1|k-1)(-1+\cos\hat{\omega}(k-1)T)}{\hat{\omega}(k-1)^2},$$

$$f_{\omega,2} = -T\hat{\dot{\xi}}(k-1|k-1)\sin\hat{\omega}(k-1) - T\hat{\dot{\eta}}(k-1|k-1)\cos\hat{\omega}(k-1)$$

$$f_{\omega,3} = \frac{T\hat{\dot{\xi}}(k-1|k-1)\sin\hat{\omega}(k-1)T}{\hat{\omega}(k-1)} - \frac{\hat{\dot{\xi}}(k-1|k-1)(1-\cos\hat{\omega}(k-1)T)}{\hat{\omega}(k-1)^2} + \frac{T\hat{\dot{\eta}}(k-1|k-1)\cos\hat{\omega}(k-1)T}{\hat{\omega}(k-1)} - \frac{\hat{\dot{\eta}}(k-1|k-1)\sin\hat{\omega}(k-1)T}{\hat{\omega}(k-1)^2},$$

$$f_{\omega,4} = T\hat{\dot{\xi}}(k-1|k-1)\cos\hat{\omega}(k-1) - T\hat{\dot{\eta}}(k-1|k-1)\sin\hat{\omega}(k-1)$$

4. SIMULATIONS RESULTS

As described in this section, we considered a state estimation problem of a vehicle in two dimensions. Simulations were executed to compare the performance of both IMM algorithms with the EKF and the nonlinear IF, respectively, for curvilinear motions. The performance of the two algorithms was compared with the use of Monte Carlo simulations. The maneuvering vehicle trajectories were generated using the various patterns mentioned in Section 2.1. Two kinematic models were used to track the maneuvering vehicle: A constant-velocity model for rectilinear motion and a constant- speed turn model for curvilinear motion. We then compare the performance of two different IMM algorithms with these two models.

4.1 The driving scenarios

It was assumed that the vehicle moves rectilinearly in the beginning. The target initial positions and velocities were differently set for each scenario. The single-target track of the maneuvering vehicle was also assumed to have been previously initialized and that track maintenance was the goal of the IMM algorithms.

i) Scenario for straight line and curve: The target initial positions and velocities were (x_0 = 0 m, y_0 = 0 m, $\dot{x}_0$ = 28 m/s, $\dot{y}_0$ = 28 m/s, ω = 0°). Its trajectory was a constant velocity between 0 s and 19 s with a speed of 28 m/s; a turn with a constant yaw rate of ω = 3.74 °/s between 20 s and 59 s; a constant velocity between 60 s and 89 s; a turn with a constant yaw rate of ω = 3.74 °/s between 90 s and 129 s; a constant velocity between 130 s and 149 s; a turn with a constant yaw rate of ω = 3.74 °/s between 150 s and 200 s.

ii) Cut-in/out scenario: The target initial positions and velocities were (x_0 = 0 m, y_0 = 20 m, $\dot{x}_0$ = 28 m/s, $\dot{y}_0$ = 0 m/s, ω = 0°). Its trajectory was a straight line between 0 s and 19 s with a speed of 28 m/s; a turn with a constant yaw rate of ω = 3.74 °/s between 20 s and 39 s; a constant velocity between 40 s and 41 s with a speed of 28 m/s; a turn between 42 s and 63 s with a yaw rate of ω = 3.74 °/s; a straight line between 64 s and 134 s with a speed of 28 m/s; a turn with a constant yaw rate of ω = 3.74 °/s between 135 s and 154 s; a constant velocity between 155 s and 159 s with a speed of 28 m/s; a turn between 160 s and 179 s with a yaw rate of ω = 3.74 °/s and a straight line between 180 s and

200 s.

iii) U-turn scenario: The target initial positions and velocities were (x_0 = 10 m, y_0 = 10 m, $\dot{x}_0$ = 28 m/s, $\dot{y}_0$ = 0 m/s, ω = 0°). This scenario included a non-maneuvering driving mode during scans from 1 s to 60 s with a speed of 28 m/s, a 180°-turn, lasting from scan 61 s to 145 s with a yaw rate of ω = 3.74 °/s , and a non-maneuvering driving mode from scan 146 s to 200 s.

iv) Interchange scenario: The target initial positions and velocities were (x_0 = 0 m, y_0 = 0 m, $\dot{x}_0$ = 28 m/s, $\dot{y}_0$ = 0 m/s, ω = 0°). This scenario included a non-maneuvering driving mode during scans from 1 s to 40 s with a speed of 28 m/s, a 270°-turn, lasting from scan 41 s to 168 s with a yaw rate of ω = 3.74 °/s , and a non-maneuvering driving mode from scan 169 s to 200 s. The maneuvering vehicle speed was 28 m/s.

4.2 Parameters used in the design

The parameters used in the design are listed here. Subscripts "CV" and "CST" stand for "constant velocity" and "constant speed turn," respectively. The initial yaw rate of the driving scenarios was $\omega(0)$ = 3 °/s . The error covariances of the initial state and covariances of process noise were as follows:

CV mode: $P^{\mathrm{KF}}(0) = \mathrm{diag}\{100\ 100\ 100\ 100\}$,

$$Q^{\mathrm{KF}} = (0.001)^2 \mathrm{I},$$

CST mode:

$$P^{\mathrm{EKF}}(0) = P^{\mathrm{nonlinear\ IF}}(0) = \mathrm{diag}\{100\ 100\ 100\ 100\ \sigma_\omega^2\},$$

$$Q^{\mathrm{EKF}} = Q^{\mathrm{nonlinear\ IF}} = \mathrm{diag}\{(0.25)^2\ (0.25)^2\ (0.25)^2\ (0.25)^2\ \sigma_\omega^2\}$$

where $\sigma_\omega = (0.01)°/\mathrm{s}$. The measurement noise covariance matrix was calculated as $\sigma_\xi = 10\mathrm{m}$ and $\sigma_\eta = 10\mathrm{m}$.

The transition probabilities for the IMM algorithms using the EKF and the nonlinear IF, respectively, were represented in the Markov chain transition matrix

$$\pi_{ij}{}^{\mathrm{EKF}} = \pi_{ij}{}^{\mathrm{UKF}} = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix} \pi_{ij}.$$

The initial mode probability vectors μ were chosen as follows:

$$\mu^{\mathrm{UKF}} = \mu^{\mathrm{UKF}} = \begin{bmatrix} 0.8 \\ 0.2 \end{bmatrix}.$$

4.3 Performance evaluation and analysis

The RMSE of each state component was chosen as the measure of performance.The performance of the IMM algorithm with an EKF and that of the IMM algorithm with a nonlinear IF are shown in Fig. 2 - Fig. 5, where the RMSE in the position and the velocity are plotted. The results presented here are based on 100 Monte Carlo runs. First of all, it is evident that the suggested algorithm has almost equal position and velocity estimation accuracy for all scenarios. The position RMSE of the IMM with a nonlinear IF is evidently close to that of the IMM with an EKF. In addition, the IMM algorithm with a nonlinear IF is characterized by low-peak dynamic errors and a short response time.

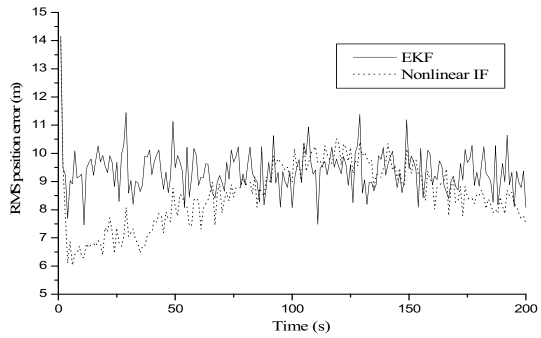

Fig. 2 Comparison of the position errors in the case of u-turn.

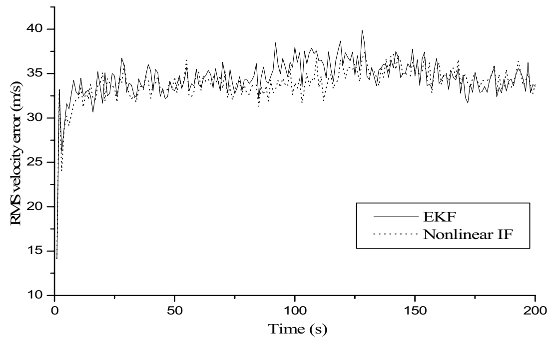

Fig. 3 Comparison of the velocity errors in the case of u-turn.

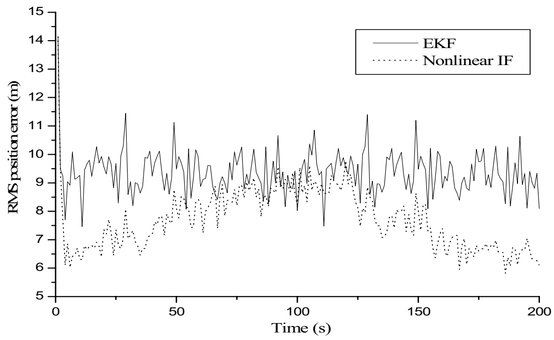

Fig. 4 Comparison of the position errors in the case of interchange.

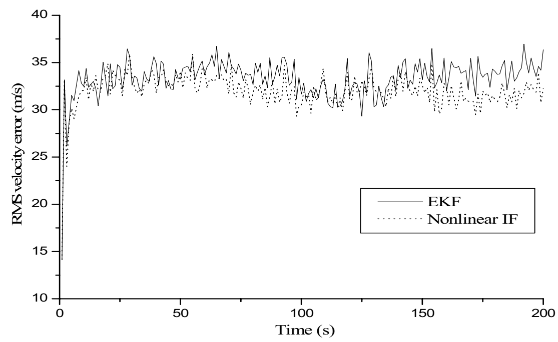

Fig. 5 Comparison of the velocity errors in the case of interchange.

5. CONCLUSIONS

In this paper, an interacting multiple model algorithm, as a tracking algorithm, to track maneuvering vehicles on a road was designed. As models to track the maneuvering vehicles, two kinematic models were derived: The constant velocity model for linear motion and the constant-speed turn model for curvilinear motion. For constant-speed turn model, a nonlinear information filter was used in place of the extended Kalman filter in nonlinear systems. The suggested algorithm reduced the root mean square error for linear motions, and it could rapidly detect possible turning motions.

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