An Improved Multi-target Tracking Algorithm for Automotive Radar

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Abstract. An improved multi-target tracking algorithm for automotive radar is proposed in this paper. In the application of automotive radar, in addition to the motion generated by the target maneuver, the maneuver of the radar-equipped vehicle will also cause the target to move relative to the radar. A single motion model for the target cannot accurately describe the motion state of the target relative to the radar. To solve the above problems, the nonlinear state equations of various motion models and their process noise covariance matrix are derived, and the Interacting Multiple Model (IMM) algorithm, the Joint Probabilistic Data Association (JPDA) algorithm and the Unscented Kalman Filter with Doppler measurement (DUKF) are combined. At the same time, the correlation coefficient of range measurement error and velocity measurement error of Frequency Modulated Continuous Wave (FMCW) radar is derived, and the relationship between it and FMCW radar parameters is studied. By simulation, its influence on target tracking is assessed, final results indicate the reference value for the application of automotive radar in intelligent driving.

1. Introduction

In recent years, with the rapid development of intelligent driving technology, mmWave radar is becoming more and more important in automotive sensors because of its high-resolution measurement, low power, low complexity and all-weather, day-or-night operation [1]. Therefore, the corresponding signal processing technology has also been rapidly developed. Since it can simultaneously and unambiguously measure the range and velocity information of the target, the Frequency Modulated Continuous Wave (FMCW) waveform is widely used. Target tracking is the main function of the automotive radar, which enables the automotive radar to obtain the target's movement trajectory for the recognition of the target's movement state (such as lane keep, lane change and curve entry/exit).

In the past few decades, there have been many researches on filtering algorithms for target tracking. Kalman Filter (KF) and its improved algorithms, such as Extended KF (EKF), Unscented KF (UKF), Cubature KF (CKF) and Particle Filters (PF) have been proposed. KF is the optimal solution of a linear system, and other algorithms can be used for nonlinear systems. However, in actual use, EKF is sensitive to the degree of non-linearity of the system; PF has high computational complexity and is not suitable for real-time use in vehicles; CKF is more used for high-dimensional non-linear systems. At present, the target tracking of the non-linear system of the automotive radar mostly uses the UKF [2].

Motion model occupies an important position in target tracking system. In [3], six motion models applicable to automotive radar are described and compared, among which Constant Turn Rate and Acceleration (CTRA) model is widely used because its state equation is very similar to the actual vehicle driving state and its calculation amount is moderate. In [4], the performance of the CTRA, Constant
Velocity (CV), and Constant Acceleration (CA) models in a multi-target tracking scenarios is compared, and the combination of CTRA and the Joint Probabilistic Data Association (JPDA) algorithms can be used to obtain the best performance in a multi-target tracking scenarios.

However, when the target is manoeuvring, especially when the target maneuver is caused by the maneuvering of radar-equipped vehicle, a single model cannot accurately describe the target's motion state, which will lead to the instability and accuracy of the target tracking system, and in severe cases, it will lead to the failure of target tracking [5]. Aiming at this problem, a method to estimate the process noise covariance matrix of motion model is proposed in [6]. However, it is difficult to use this method in practice if the results of this method need to be adjusted artificially in order to obtain good tracking accuracy. At present, the real-time multi-target tracking mostly uses IMM-JPDA algorithm, which combines the advantages of the Interacting Multiple Model (IMM) algorithm and JPDA algorithm, and is an effective algorithm in line with the actual needs [7].

The IMM-JPDA-DUKF algorithm proposed in this paper combines the advantages of the IMM-JPDA algorithm, IMM-UKF algorithms and the Unscented Kalman Filter with Doppler measurement (DUKF), and is a tracking algorithm suitable for multiple manoeuvring target environments and nonlinear systems. In this paper, the nonlinear state equations and process noise covariance matrices of CV, CA and CTRA models are derived, and them are used in the IMM-JPDA-DUKF algorithm. In addition, the influence of FMCW radar parameters on target tracking performance is also assessed. The remainder of this paper is organized as follows. In Section 2, the range, velocity measurement and correlation coefficients of FMCW radar is derived. In Section 3, the IMM-JPDA-DUKF algorithm and motion model are presented. Section 4 presents the simulation result of contents of the first two section. Section 5 summarizes the achievements and research contributions of this paper.

2. FMCW radar parameter estimation
The FMCW radar in this paper uses the rapid chirps waveform to estimate the range and velocity parameters of the target. The rapid chirps waveform is shown in figure 1 [8]. The range and velocity parameters of the waveform can be obtained from the range Doppler spectrum after Two-Dimensional Fast Fourier Transform (2D-FFT) of the beat frequency signal. In the range Doppler spectrum of the radar, the relationship between the measured value of the frequency and the estimation of range and velocity is as below:

\[ f_r = \frac{2B}{cT} - \frac{2f_0v}{c}, \quad f_v = -\frac{2f_0v}{c} \]  \hspace{1cm} (1)

Where, \( f_r \) and \( f_v \) are the range and velocity dimension frequency corresponding to the target respectively; \( B \) is the sweep bandwidth; \( T \) is the chirp duration; \( f_0 \) is the carrier frequency; \( c \) is the speed of light; \( r \) and \( v \) are the relative range and velocity between the target and the radar respectively. To transform equation (1), we can get:

\[ r_b = r - \frac{f_0}{K}v_b, \quad v_b = v \]  \hspace{1cm} (2)

\( r_b \) and \( v_b \) are the range and velocity corresponding to the frequency of the range and velocity dimension, respectively, and \( K \) are the frequency modulation rate. From the above formula, it can be observed that there is a coupling phenomenon in the range and velocity information of the target, and there is a correlation between them. The measured value of target range and velocity obtained after decoupling can be expressed as:

\[ m_r = r_b + \frac{f_0}{K}m_v + w_r, \quad m_v = v_b + w_v \]  \hspace{1cm} (3)
In the formula, $w_r$ and $w_v$ are two independent zero-mean normal distributions with standard deviations of $\sigma_r$ and $\sigma_v$, respectively. The correlation coefficient of FMCW radar range velocity measurement error can be deduced as equation (4) [9].

$$
\rho = \frac{E[(m_r - r)(m_v - v)]}{\sqrt{E[(m_r - r)^2]E[(m_v - v)^2]}} = \frac{1}{\sqrt{1 + (\sigma_r^2/\sigma_v^2)^2}}
$$

(4)

It can be observed from (4) that the correlation coefficient $\rho$ is positive, and when $\sigma_r/\sigma_v f_0$ remains unchanged, the correlation coefficient $\rho$ decreases with the increase of $K$. In addition, it should be noted that the above derivation relies on taking the velocity of the target approaching the radar set as positive as the basis. When the velocity of the target away from the radar is set as positive, the derivation of the correlation coefficient is similar to the above under the same setting, and the final result is the negative of equation (4), that is, the correlation coefficient $\rho$ is negative at this time. With the variation of $K$, the variation of correlation coefficient $\rho$ is specifically depicted in figure 2. The influence of correlation coefficient $\rho$ on target tracking will be assessed in Section 4.

3. Multi-target tracking

For automotive radar applications, the motion state of the vehicle in front is complicated, and the driver’s wishes may cause it to maneuver at any time during its motion. For maneuvering targets, a single model, such as CA, CV, CTRA, cannot provide an accurately state estimation when the target is maneuvering, resulting in a decrease in target tracking accuracy or even tracking failure. In order to achieve multi-target tracking of maneuvering targets, the IMM-JPDA algorithm combining IMM algorithm and JPDA algorithm is proposed. However, the effect of this algorithm in the nonlinear case is far less than in the linear case. In order to solve this problem, DUKF is introduced. The tracking position and velocity errors of DUKF relative to UKF are both smaller. The flow chart of the IMM-JPDA-DUKF algorithm in this article is shown in figure 3.

3.1. IMM-JPDA-DUKF algorithm

In figure 3, $X^0_k$ represents the state estimation of the $j$-th ($j = 1, ..., M$) filter for the $t$-th ($t = 1, ..., N$) target at frame $k$; $X^t_k$ is the status update of target $t$ at frame $k$; $Z(k)$ is the candidate measurement set in the target correlation gate at frame $k$; $u_{\phi}(k)$ is the model probability of the $j$-th model of the $t$-th target at frame $k$; $\Lambda_{\phi}(k)$ is the likelihood probability of target $t$ for model $j$ at frame $k$. The steps of IMM-JPDA-DUKF algorithm are as follows:
The interaction of state estimation: the filter \( j \) input of target \( t \) after interaction is
\[
X_{k-1}^{ojj} = \sum_{i=1}^{M} X_{k-1}^{ij} u_{ij}^{k-1} P_{k-1}^{ij} = \sum_{i=1}^{M} \{ P_{k-1}^{ij} + [X_{k-1}^{ij} - X_{k-1}^{ojj}][X_{k-1}^{ij} - X_{k-1}^{ojj}]'^{1/2} \} u_{ij}^{k-1}
\]  \( (5) \)

State prediction: Use DUKF filter for state prediction. DUKF is discussed in detail in [10], and the nonlinear motion model is
\[
X_{k|k-1}^{ojj} = f(X_{k-1}^{ojj})
\]  \( (6) \)

Data association: the validation gate of target \( t \) is determined by model \( j \) with the largest determinant of the residual covariance matrix. Probability update of target association and target state update are discussed in detail in [11].

Likelihood function update: the likelihood function of the target \( t \) for model \( j \) is
\[
\Lambda_y = \gamma^{-v_{y}/2} \frac{m_k}{c_s P_D |S_{y}|^{v_{y}/2}} \left( 1 - P_y P_{y} \right) + \sum_{i=1}^{m_y} N[v_{y}^{i}; 0, S_{y}^{i}]
\]  \( (7) \)

\( P_D \) is the detection probability, \( m_k \) is the number of measurement points in the target \( t \) validation gates. \( P_G \) is the true measure of the probability of falling into the validation gate.

Model probability update and target state output: According to the likelihood function, the state vector of target \( t \) at frame \( k \) is
\[
u_{y}(k) = \frac{1}{c} \Lambda_y \sum_{j=1}^{M} P_y^{i} u_{yj}^{i (k-1)} \quad X_{k}^{i} = \sum_{j=1}^{M} X_{k}^{ij} u_{yj}^{i (k)}
\]  \( (8) \)

\( c \) is the normalization constant, \( P_y^{i} \) is the transition probability of target \( t \) from model \( i \) to model \( j \).

Compared with the JPDA algorithm, the IMM-JPDA-DUKF algorithm has better accuracy and stability when the target is maneuvering. The measurement of FMCW radar is carried out in the polar coordinate system, and the use of DUKF can make this algorithm compared with the use of sequential filter to avoid the conversion measurement and the range and velocity measurement of the decorrelation operation, and better adaptability and stability of nonlinear system [12].

### 3.2. Motion model

Model sets play an important role in target tracking, and a suitable motion model can bring higher accuracy for target tracking. At present, in addition to the traditional CV and CA models, the motion models suitable for automotive radar applications also include CTRA, Constant Steering Angle and velocity (CSAV) and Constant Curvature and Acceleration (CCA) models. Consider the applicable
scope and performance of each model. The IMM algorithm in this paper includes CV, CA and CTRA motion models. In order to make CV, CA model and CTRA model used in IMM simultaneously, some transformations of CV, CA models are carried out and the process noise covariance matrix of the transformed model is derived in this paper. The prediction equation of the motion model contained in IMM is as follows [13]:

\[
\begin{align*}
    f_{CV} &= \begin{bmatrix}
    v(t) \cos(\theta(t)) \\
    v(t) \sin(\theta(t)) \\
    0 \\
    0
    \end{bmatrix},
    f_{CA} &= \begin{bmatrix}
    v(t) \cos(\theta(t)) \\
    v(t) \sin(\theta(t)) \\
    a(t) \\
    0
    \end{bmatrix},
    f_{CTRA} &= \begin{bmatrix}
    v(t) \cos(\theta(t)) \\
    v(t) \sin(\theta(t)) \\
    a(t) \\
    \omega(t)
    \end{bmatrix}
\end{align*}
\]

(9)

\( v(t) \) is the velocity and \( \theta(t) \) is the yaw angle. The discrete-time motion model is derived as:

\[
X_{k+1} = X_k + f(x(t)) dt
\]

(10)

The motion model is as follows, the CV model:

\[
\begin{align*}
    x(k+1 | k) &= x(k | k) + v(k | k) \cos(\theta(k | k) T) + 0.5a(k | k) \cos(\theta(k | k) T)^2 \\
    y(k+1 | k) &= y(k | k) + v(k | k) \sin(\theta(k | k) T) + 0.5a(k | k) \sin(\theta(k | k) T)^2 \\
    \theta(k+1 | k) &= \theta(k | k) + \omega(k | k) T \\
    v(k+1 | k) &= v(k | k) + a(k | k) T \\
    a(k+1 | k) &= a(k | k) \\
    \omega(k+1 | k) &= \omega(k | k)
\end{align*}
\]

(11)

The CTRA model:

\[
\begin{align*}
    x(k+1 | k) &= x(k | k) + \left( v(k | k) \cos(\theta(k | k) T) - v(k | k) \sin(\theta(k | k) T) \right) + a(k | k) \cos(\theta(k | k) T) + a(k | k) \sin(\theta(k | k) T) + a(k | k) \\
    y(k+1 | k) &= y(k | k) + \left( v(k | k) \sin(\theta(k | k) T) + v(k | k) \cos(\theta(k | k) T) \right) + a(k | k) \cos(\theta(k | k) T) - a(k | k) \sin(\theta(k | k) T) + a(k | k) \\
    \theta(k+1 | k) &= \theta(k | k) + \omega(k | k) T \\
    v(k+1 | k) &= v(k | k) + a(k | k) T \\
    a(k+1 | k) &= a(k | k) \\
    \omega(k+1 | k) &= \omega(k | k)
\end{align*}
\]

(13)

The observation data of the vehicle-mounted FMCW radar includes the parameters of range \( (Z_r) \), angle \( (Z_\theta) \) and velocity \( (Z_v) \). Therefore, the nonlinear observation equation for target tracking is expressed as:

\[
\begin{align*}
    Z_r(k+1 | k) &= \sqrt{x^2(k+1 | k) + y^2(k+1 | k)} \\
    Z_\theta(k+1 | k) &= \arctan\left(\frac{y(k+1 | k)}{x(k+1 | k)}\right) \\
    Z_v(k+1 | k) &= -(v(k+1 | k) \cos(\theta(k+1 | k)) \cos(Z_r(k+1 | k)) + v(k+1 | k) \sin(\theta(k+1 | k)) \sin(Z_r(k+1 | k)))
\end{align*}
\]

(14)

and when the radial velocity of the target away from the radar is set as positive, the negative sign of \( Z_v(k+1 | k) \) should be removed. The measurement noise covariance matrix of FMCW radar can be expressed as:

\[
R(k+1) = \begin{bmatrix}
    \sigma_r^2 & 0 & \rho \sigma_r \sigma_v \\
    0 & \sigma_\theta^2 & 0 \\
    \rho \sigma_r \sigma_v & 0 & \sigma_v^2
\end{bmatrix}
\]

(15)
Figure 4. RMSE of target tracking under different correlation coefficients $\rho$, (a) range RMSE, (b) velocity RMSE.

Figure 5. RMSE of Target Tracking of Target vehicle 2, (a) range RMSE, (b) velocity RMSE.

The process noise covariance matrix of CV, CA and CTRA models in this paper can be derived as [14]:

$$
\Gamma_{CV} = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}^T, \Gamma_{CA} = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}^T, \Gamma_{CTRA} = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}^T
$$

$$
Q_{CV} = \begin{bmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_r^2 \end{bmatrix}, Q_{CA} = \begin{bmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_r^2 \end{bmatrix}, Q_{CTRA} = \begin{bmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_r^2 \end{bmatrix}
$$

$$
Q_k = \int_0^t e^{\int_0^t \Gamma^T Q \Gamma^T (e^{\int_0^t \Gamma^T Q \Gamma^T})^T d\tau} e^{At} \Delta \sum_{i=0}^{\infty} \frac{(At)^i}{i!} \approx I + At + \frac{At^2}{2}.
$$

$\nabla f$ is the Jacobian matrix of $f$, $Q_k$ is the process noise covariance matrix of the motion model.

4. Simulation results

4.1. The impact of correlation coefficient $\rho$ on target tracking

To evaluate the effects of the correlation coefficient $\rho$ of target tracking, this section for different correlation coefficient $\rho$ of target tracking performance 200 times Monte Carlo simulation. The simulation environment in this section is $\sigma_r = 0.2m$, $\sigma_v = 2$ degree, $\sigma_v = 1km / h$, and the tracking algorithm set by the simulation is CA-DUKF. The target tracking performance under five correlation coefficients is simulated, which are $\rho = 0.9, 0.5, 0, -0.5, -0.9$ respectively. The simulation results are shown in Figure 4 and Table 1.

From figure 4 and Table 1, it can be seen that the smaller the correlation coefficient $\rho$ is, the smaller the target tracking range root mean square error (RMSE) and the smaller the range average RMSE are. And for the velocity tracking RMSE and the velocity average RMSE, the value is the largest when the correlation coefficient is zero, and as the absolute value of the correlation coefficient increases, the value continues to decrease, and when the correlation coefficient is negative, the value becomes smaller.
Table 1. Target tracking average rmse under different correlation coefficient $\rho$.

| Average RMSE          | Correlation coefficients $\rho$ |
|-----------------------|---------------------------------|
|                       | 0.9    | 0.5    | 0      | -0.5   | -0.9   |
| Range average RMSE (m) | 0.0117 | 0.0116 | 0.0115 | 0.0114 | 0.0112 |
| Velocity average RMSE (m/s) | 0.0069 | 0.0094 | 0.0098 | 0.0085 | 0.0049 |

Table 2. Average range rmse of the two algorithms.

| Range average RMSE (m) | Target vehicle 1 | Target vehicle 2 | Target vehicle 3 |
|------------------------|------------------|------------------|------------------|
| CTRA-JPDA-DUKF algorithm | 0.0069           | 0.0117           | 0.0237           |
| IMM-JPDA-DUKF algorithm   | 0.0067           | 0.0102           | 0.0272           |

Table 3. Average velocity rmse of the two algorithms.

| Velocity average RMSE (m/s) | Correlation coefficients $\rho$ |
|-----------------------------|---------------------------------|
|                            | Target vehicle 1 | Target vehicle 2 | Target vehicle 3 |
| CTRA-JPDA-DUKF algorithm    | 0.0232           | 0.0223           | 0.0258           |
| IMM-JPDA-DUKF algorithm     | 0.0099           | 0.0099           | 0.0145           |

In summary, for FMCW radar target tracking, when the absolute value of correlation coefficient is the same, the radar target tracking accuracy is higher when the correlation coefficient is negative; when the correlation coefficients are negative, the greater the absolute value of correlation coefficient is, the higher the target tracking accuracy is. In addition, when the correlation coefficient is negative, the target tracking accuracy is higher than when the correlation coefficient is zero; when the correlation coefficient is positive, the target tracking range RMSE is greater than when the correlation coefficient is zero. It can be seen that when using FMCW radar for target tracking, the velocity of the target away from the radar should be set as positive; at the same time, combined with figure 2, the lower the frequency modulation rate of the FMCW radar, the better the target tracking performance.

4.2. Performance analysis of IMM-JPDA-DUKF algorithm

This section of the simulation is carried out in a U-shaped curve scene. The simulation includes 3 target vehicles, which perform maneuvers such as changing lanes and entering and exiting curves in different lanes on the road. The parameters of simulation are set in the same section as above, correlation coefficient $\rho = -0.9$, clutter density $\lambda = 0.33$, the probability of falling into the gate of real measurement $P_g = 0.99$, the probability of target detection $P_d = 0.99$, and the number of Monte Carlo simulations is 200. The simulation results are shown in figure 5, Table 2 and Table 3. figure 5 analyzes the performance of CTRA-JPDA-DUKF algorithm and IMM-JPDA-DUKF algorithm through the tracking RMSE of the target vehicle 2. Table 2 and Table 3 assessed the average RMSE of the three simulated target vehicles, which more accurately shows the advantages and disadvantages of the two algorithms. The target maneuver of target vehicle 2 occurs when the simulation steps are 73,106,196,235,290,329,391,432. Among them, the target maneuver that occurs when the simulation steps are 235 and 329 is special, which is caused by the radar car entering and exiting the curve. As can be seen from figure 5, the range RMSE of the CTRA-JPDA-DUKF algorithm is unstable at 235 and 329 simulation steps, and the range tracking accuracy decreases seriously. This is because the target maneuver is not caused by the movement of the target vehicle, but by the movement of the radar-equipped vehicle. Therefore, the movements of the two target vehicles cannot be described by a simple
CTRA model. Compared with the CTRA-JPDA-DUKF algorithm, it can be seen from figure 5 (a) that IMM-JPDA-DUKF algorithm has certain advantages, and its simulation stability in these two places is better than that of CTRA-JPDA-DUKF algorithm, and the target range tracking accuracy is higher. This is because IMM-JPDA-DUKF algorithm uses a variety of motion models to describe the motion state of the target, which improves the stability of the target tracking system.

In addition, it can be found from figure 5(b) that the velocity RMSE of the CTRA-JPDA-DUKF algorithm is always higher than that of the IMM-JPDA-DUKF algorithm. The velocity RMSE of the CTRA-JPDA-DUKF algorithm is only close to the IMM-JPDA-DUKF algorithm when the target vehicle 2 is in the curve with the radar-equipped vehicle. At other times, the velocity tracking performance of the CTRA-JPDA-DUKF algorithm is always inferior to that of the IMM-JPDA-DUKF algorithm, and whenever the target maneuvers, its velocity tracking accuracy will be significantly reduced.

It can be seen from Table 2 that the range tracking accuracy of target vehicle 1 and target vehicle 2 of IMM-JPDA-DUKF algorithm is better than that of CTRA algorithm, but the same is not true of target vehicle 3. This is because the target vehicle 3 has high velocity and high maneuvering acceleration, and the IMM-JPDA-DUKF algorithm cannot accurately describe the target motion state, and the multi-model competition in IMM-JPDA-DUKF reduces the target range tracking accuracy to a certain extent. This problem can be improved by adjusting the model set. It can be seen from Table 3 that the velocity tracking accuracy of IMM-JPDA-DUKF algorithm is always better than CTRA-JPDA-DUKF algorithm, and the velocity tracking accuracy of IMM-JPDA-DUKF algorithm is improved by at least 40% compared with CTRA-JPDA-DUKF algorithm.

In conclusion, IMM-JPDA-DUKF algorithm has a great improvement in tracking performance, especially velocity tracking performance, compared with CTRA-JPDA-DUKF algorithm, and is a method suitable for automotive radar multi-target maneuvering target tracking.

5. Conclusions
To improve the target tracking performance of multiple maneuvering targets, an IMM-JPDA-DUKF algorithm is proposed, and the state equations and process noise covariance matrices of the nonlinear models CV, CA and CTRA included in the algorithm are derived. According to the simulation results, for multiple maneuvering targets scenarios of the automotive radar, the tracking performance, especially the velocity tracking performance, of the IMM-JPDA-DUKF algorithm is higher at least 40% than that of CTRA-JPDA-DUKF algorithm. Moreover, this algorithm can better solve the problem that single CTRA model can not accurately describe the motion state of the target vehicle when radar-equipped vehicle maneuvering, and improve the stability of tracking system.

The correlation coefficient between FMCW radar range measurement error and speed measurement error is derived, and the target tracking performance under different correlation coefficient conditions is simulated in this paper. According to the simulation results, the FMCW radar has a better target tracking performance when the velocity of the target approaching the radar is set as positive, and the frequency modulation slope is small.

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References
[1] Ciattaglia, G., Santis, A.D., Disha, D., et al. (2020) Performance Evaluation of Vibrational Measurements through mmWave Automotive Radars. In: 2020 IEEE 7th International Workshop on Metrology for AeroSpace. Italy. pp. 160-165.
[2] Dai, H.D., Dai, S.W., Cong, Y.C., et al. (2012) Performance Comparison of EKF/UKF/CKF for the Tracking of Ballistic Target. Telkomnika Indonesian Journal of Electrical Engineering, 10: 1692-1699.
[3] Schubert, R., Richter, E., Wanielik, G. (2008) Comparison and evaluation of advanced
motion models for vehicle tracking. In: the 11th International Conference on Information Fusion. Cologne. pp. 1-6.

[4] Eltrass, A., Khalil, M. (2018) Automotive radar system for multiple-vehicle detection and tracking in urban environments. IET Intelligent Transport Systems., 12: 783-792.

[5] Shi, K., Cheng, D., et al. (2020) Interacting multiple model-based adaptive control system for stable steering of distributed driver electric vehicle under various road excitations. ISA Transactions., 103: 37-51.

[6] Saho, K., Masugi, M. (2015) Automatic Parameter Setting Method for an Accurate Kalman Filter Tracker Using an Analytical Steady-State Performance Index. IEEE Access., 3: 1-1.

[7] Meliones, A., Pappas, D. (2020) Data Fusion and Tracking in a Simulated Multiradar Air Command and Control System. Sensing and Imaging., 21: 1-24.

[8] Zheng, Q., Yang, L., Xie, Y., et al. (2021) A Target Detection Scheme With Decreased Complexity and Enhanced Performance for Range-Doppler FMCW Radar. IEEE Transactions on Instrumentation and Measurement., 70: 1-13.

[9] Bruno, L., Braca, P., et al. (2013) Experimental Evaluation of the Range–Doppler Coupling on HF Surface Wave Radars. Geoscience and Remote Sensing Letters., 10: 850-854.

[10] Xiong, K., Zhang, H.Y., Chan, C.W. (2006) Performance evaluation of UKF-based nonlinear filtering. Automatica., 42:261-270.

[11] Yeom, S. (2008) Efficient multi-target tracking with sub-event IMM-JPDA and one-point prime initialization. In: the International Conference on Multisensor Fusion and Integration for Intelligent Systems 2008. Seoul. pp. 712-714.

[12] Fu, J., Sun, J., Lu, S., et al. (2016) Debiased converted position and Doppler measurement tracking with array radar measurements in direction cosine coordinates. IET Radar Sonar & Navigation., 10: 155-165.

[13] Rongli, X., Jilkov, V.P. (2003) Survey of maneuvering target tracking. Part I: Dynamic models. IEEE Transactions on Aerospace and Electronic Systems., 39(4).

[14] Svensson, D. (2019) Derivation of the discrete-time constant turn rate and acceleration motion model. In: 2019 Sensor Data Fusion: Trends, Solutions, Applications (SDF). Bonn. pp. 1-5.