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De-correlated unbiased sequential filtering based on best unbiased linear estimation for target tracking in Doppler radar

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Abstract: In target tracking applications, the Doppler measurement contains information of the target range rate, which has the potential capability to improve the tracking performance. However, the nonlinear degree between the measurement and the target state increases with the introduction of the Doppler measurement. Therefore, target tracking in the Doppler radar is a nonlinear filtering problem. In order to handle this problem, the Kalman filter form of best linear unbiased estimation (BLUE) with position measurements is proposed, which is combined with the sequential filtering algorithm to handle the Doppler measurement further, where the statistic characteristic of the converted measurement error is calculated based on the predicted information in the sequential filter. Moreover, the algorithm is extended to the maneuvering target tracking case, where the interacting multiple model (IMM) algorithm is used as the basic framework and the model probabilities are updated according to the BLUE position filter and the sequential filter, and the final estimation is a weighted sum of the outputs from the sequential filters and the model probabilities. Simulation results show that compared with existing approaches, the proposed algorithm can realize target tracking with preferable tracking precision and the extended method can achieve effective maneuvering target tracking.

Keywords: Kalman filter, best linear unbiased estimation (BLUE), measurement conversion, sequential filter.

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1. Introduction

In radar tracking application, the target dynamics are usually described in Cartesian coordinates while the measurements are obtained from the original radar coordinates directly. Therefore, tracking is performed in mixed coordinates, which leads to actually a nonlinear state estimation problem. For a practical radar, in particular the Doppler radar or the ground moving target indication (GMTI) radar, the Doppler measurement can also be provided. The tracking accuracy can be greatly improved by effective utilization of the Doppler information of the target [1,2], but the measurement model is more complex substantially when the Doppler measurement is involved [3], and the nonlinear degree between the measurement and the target state increases in this case. There are many types of methods commonly used to realize target tracking with nonlinear measurement [4−7], including the extended Kalman filter (EKF), the unscented Kalman filter (UKF) and the particle filter (PF). In the EKF, the nonlinear measurement function is approximated by the linear part of its Taylor expansion. Therefore, EKF is not good at approximating the strong nonlinearity. The UKF uses a minimum set of sample points to approximate the system state distribution, which is more accurate than the EKF, but the algorithm is more complex. The PF can solve the nonlinear filtering problem effectively and it performs well in the strong nonlinear case. However, the PF has the disadvantage of large computational complexity. Besides the above methods, to deal with the nonlinearity in the measurement equation, many measurement conversion methods were proposed [8−11]. The measurements in the radar (polar or spherical) coordinates are converted to the Cartesian coordinates through different conversion methods. Then, the mean and corresponding covariance matrices of the converted error are calculated. Under the condition of a steady state stationary, the $\alpha-\beta$ filter can be applied with the measurement conversion method [12] to solve the nonlinear target tracking problem. When the range rate measurement is available, the pseudo measurement produced by the product of range and range rate can be used to reduce the nonlinearity, which can be processed sequentially to improve the tracking accuracy [13, 14]. The pseudo state related to the range rate was introduced in the statically fused (SF) method [15,16], where the position state estimation and pseudo state estimation

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were combined by a static minimum mean squared error estimator (MMSE). To improve the performance of the converted measurement method, a novel multiplicative unbiased converted measurement Kalman filter algorithm with range rate (UCMKF-R) was developed in [17]. An unbiased and consistent measurement conversion from range, bearing, and range rate to the Cartesian position and velocity with appropriate elimination of estimation bias was proposed in [18]. For the measurements reported in the direction cosine coordinates (COS), an effective tracking method named sequential extended Kalman filter (SEKF) using de-biased converted position and Doppler measurements in the COS (DCMSEKFcos) was proposed in [19]. To resolve the nonlinear estimation problem in the bistatic radar tracking system, the converted measurement sigma point Kalman filter (CMSPKF) [20] estimates the conversion bias and the converted measurement error covariance with a sigma point transform (SPT) using a combination of the tracker's predicted estimate and the raw measurement error covariance. On the other hand, the best linear unbiased estimation (BLUE) can directly derive the form of the linear filter under the MMSE criterion for the nonlinear measurements [21]. Considering the tracking with the range rate, the recursive BLUE with the range rate was proposed in [22]. Another BLUE-related filtering method with the range rate was the one that introduced the conventional BLUE into the statically fusion method in [23].

Besides the nonlinear measurement, most targets have maneuvering characteristics in practice and model-mismatch is inevitable with the single target state model in filtering processing. Recently, numerous works have been done concerning the maneuvering target tracking problem. The research in this field includes the adaptive single model filter based on maneuver identification and detection, such as “current” statistical model [24], input estimation (IE), variable dimension filter [25], etc., and the ones based on multiple models, such as multiple-model algorithm, interacting multiple model (IMM) algorithm, and variable structure IMM algorithm [26]. The IMM algorithm essentially provides an algorithm framework that is easy to combine with the conventional tracking algorithm based on a single model, and meanwhile the IMM approach can achieve quick transition between the target modes. For IMM-based nonlinear measurement filtering methods, the modified IE (MIE) and the BLUE filter are fused within the IMM framework to achieve the accuracy and robustness of maneuvering target tracking [27]. In [28], the covariance intersection (CI) fusion algorithm based on the BLUE filter within the IMM framework was proposed to realize target tracking with multiplatform. In [29], a sequential maneuver detector was developed based on the Neyman Pearson criterion to overcome threshold shifting which results from the maneuver detection delay, where the Doppler measurement is utilized to solve the optimization problem based on the Mahalanobis distance. While the aforementioned works have made definite contributions to the classical problems of nonlinear measurement and maneuvering target tracking, the current methods have not achieved satisfactory results and there are still some issues to be addressed:

(i) In existing nonlinear measurement algorithms [8−10], the error statistics are derived on the condition of the measurement information, which will result in a nonlinear biased estimation. Although the derivation based on predicted information was proposed in [11] to avoid the above mentioned problem, it does not consider the effective utilization of the Doppler information. The sequential nonlinear tracking filter with Doppler information was proposed in [13,14] to deal with the strong nonlinearity of the range rate. However, the error statistics in these methods are still based on the measurement information. In summary, the existing nonlinear measurement algorithms cannot deal with the biased estimation and the range rate simultaneously.

(ii) BLUE is regarded as a method different from the converted measurement Kalman filter (CMKF). The relation between the two types of nonlinear filtering algorithms is not investigated. It gives us an idea whether there is a relationship between the CMKF and the BLUE filter that can be utilized.

(iii) Most of the existing nonlinear filtering algorithms are proposed for un-maneuvering target tracking, not considering the maneuvering characteristics of targets. IMM-based filtering methods were proposed in [27] for maneuvering target tracking with the nonlinear measurement. However, the above algorithms just take the target position into consideration, which cannot handle the range rate appropriately.

Based on above, de-correlated unbiased sequential (DUSQ) filtering is proposed for target tracking with the nonlinear measurement. The main contributions are as follows:

(i) DUSQ filtering is derived, in which the statistics of the converted pseudo measurement is calculated based on the predicted information to avoid the drawbacks based on the measurement information.

(ii) The relationship between BLUE and CMKF is investigated. The Kalman filter form of BLUE with the position measurement is obtained, which is combined with the sequential filtering algorithm based on the converted pseudo measurement further.

(iii) DUSQ is extended to the maneuvering target tracking case, where it is combined with the IMM algorithm. The model probabilities are obtained according to the estimation results from the BLUE position filter and the sequential filter. Therefore, the accuracy of model probabilities can be improved.

The rest of this paper is organized as follows. The problem is formulated in Section 2. The Kalman filter form of BLUE with position measurements is presented in Section 3. The sequential filtering based on BLUE with the additional Doppler measurement is given in Section 4. In Section 5, the IMM BLUE sequential filtering algorithm for maneuvering target tracking is presented. The Monte Carlo simulation results are shown in Section 6, followed by conclusions in Section 7.

2. Problem formulation

In most cases, the range and angle measurements can be obtained from the radar system. The measurement equation has the nonlinear form as in (1) due to different coordinate systems between the state and the measurement.

$$[r_k^m,\theta_k^m,\varepsilon_k^m]^{\mathrm{T}} = h(x_k)+v_k = [r_k,\theta_k,\varepsilon_k]^{\mathrm{T}}+v_k = \left[\sqrt{x_k^2+y_k^2+z_k^2}\ \arctan\frac{y_k}{x_k}\ \arctan\frac{z_k}{\sqrt{x_k^2+y_k^2}}\right]+v_k \tag{1}$$

where (x_k,y_k,z_k) is the true position in the Cartesian coordinates. The measured range r_k^m, bearing θ_k^m and elevation ε_k^m are defined with respect to the true range r_k, bearing θ_k and elevation ε_k of the target in spherical coordinates. The measurement noise sequence is $\boldsymbol{v}_k = [\widetilde{r}_k,\widetilde{\theta}_k,\widetilde{\varepsilon}_k]^{\mathrm{T}}$, where $\widetilde{r}_k$, $\widetilde{\theta}_k$ and $\widetilde{\varepsilon}_k$ are assumed to be additive measurement noise with zero means and standard deviations σ_r, σ_θ and σ_ε, respectively.

In the Doppler radar, the additional range rate measurement can be obtained with

$$\dot{r}_k^m = \dot{r}_k + \widetilde{\dot{r}}_k \tag{2}$$

where $\dot{r}_k$ is the true range rate of the target.

$$\dot{r}_k = \frac{x_k\dot{x}_k + y_k\dot{y}_k + z_k\dot{z}_k}{r_k} \tag{3}$$

where $(\dot{x}_k,\dot{y}_k,\dot{z}_k)$ is the true velocity in the Cartesian coordinates. The measurement noise $\widetilde{\dot{r}}_k$ is assumed to be Gaussian distribution with zero means and standard deviations $\sigma_{\dot{r}}$. The correlation coefficient between $\widetilde{r}_k$ and $\widetilde{\dot{r}}_k$ is ρ.

Note that the nonlinear relationship between the state, the measurement and the Kalman filter is valid only for the linear system with white uncorrelated noise. The problem here is how to use the nonlinear measurements to estimate the target state.

3. Kalman filter form of BLUE with position measurements

The recursive BLUE filter is in general valid for a nonlinear as well as linear model. In this part, the recursive BLUE filter and its Kalman form deviations are given. Suppose that the target state estimations are $\widehat{\boldsymbol{x}}_{k-1}$ and $\boldsymbol{P}_{k-1}$ at time $k-1$, and $\boldsymbol{Z}^k$ is the historical measurement data until the moment k. Based on the measurement model in (1), the recursive form of the BLUE filter is given as follows [21].

(i) Prediction

The predicted state $\overline{\boldsymbol{x}}_k$ and the corresponding error covariance $\overline{\boldsymbol{P}}_k$ are

$$\overline{\boldsymbol{x}}_k = \left[\overline{x}_k\ \overline{\dot{x}}_k\ \overline{y}_k\ \overline{\dot{y}}_k\ \overline{z}_k\ \overline{\dot{z}}_k\right]^{\mathrm{T}} = \boldsymbol{F}_{k-1}\widehat{\boldsymbol{x}}_{k-1} + \boldsymbol{\Gamma}_{k-1}\overline{\boldsymbol{w}}_{k-1} \tag{4}$$

where $\boldsymbol{F}_{k-1}$ is the state transfer matrix, $\overline{\boldsymbol{w}}_{k-1}$ is the process noise and $\boldsymbol{\Gamma}_{k-1}$ is the input matrix of $\overline{\boldsymbol{w}}_{k-1}$.

$$\begin{gathered}\overline{\boldsymbol{P}}_k = \mathrm{cov}\left[\boldsymbol{x}_k - \overline{\boldsymbol{x}}_k|\boldsymbol{Z}^{k-1}\right] = \\ \left[\mathrm{cov}(\widetilde{\boldsymbol{x}}_k,\widetilde{x}_k),\mathrm{cov}\left(\widetilde{\boldsymbol{x}}_k,\widetilde{\dot{x}}_k\right),\mathrm{cov}(\widetilde{\boldsymbol{x}}_k,\widetilde{y}_k),\right. \\ \left.\mathrm{cov}\left(\widetilde{\boldsymbol{x}}_k,\widetilde{\dot{y}}_k\right),\mathrm{cov}(\widetilde{\boldsymbol{x}}_k,\widetilde{z}_k),\mathrm{cov}\left(\widetilde{\boldsymbol{x}}_k,\widetilde{\dot{z}}_k\right)\right] = \\ \boldsymbol{F}_{k-1}\boldsymbol{P}_{k-1}\boldsymbol{F}_{k-1}^{\mathrm{T}} + \boldsymbol{\Gamma}_{k-1}\boldsymbol{Q}_{k-1}\boldsymbol{\Gamma}_{k-1}^{\mathrm{T}}\end{gathered} \tag{5}$$

where $\widetilde{\boldsymbol{x}}_k = \boldsymbol{x}_k - \overline{\boldsymbol{x}}_k = \left[\widetilde{x}_k\ \widetilde{\dot{x}}_k\ \widetilde{y}_k\ \widetilde{\dot{y}}_k\ \widetilde{z}_k\ \widetilde{\dot{z}}_k\right]^{\mathrm{T}}$, $(\overline{x}_k,\overline{y}_k,\overline{z}_k)$ and $(\overline{\dot{x}}_k,\overline{\dot{y}}_k,\overline{\dot{z}}_k)$ are the predicted position and velocity in the Cartesian coordinates, respectively. $\boldsymbol{Q}_{k-1}$ is the covariance matrix of $\overline{\boldsymbol{w}}_{k-1}$.

(ii) Update

$$\widehat{\boldsymbol{x}}_k^p = \mathrm{E}^*\left[\boldsymbol{x}_k|\boldsymbol{Z}^k\right] = \boldsymbol{x}_k + \boldsymbol{K}_k(z_k^p - \overline{z}_k^p), \tag{6}$$

$$\boldsymbol{P}_k^p = \overline{\boldsymbol{P}}_k - \boldsymbol{K}_k\boldsymbol{S}_k\boldsymbol{K}_k^{\mathrm{T}}, \tag{7}$$

where $\mathrm{E}^*[\boldsymbol{x}_k|\boldsymbol{Z}^k]$ represents the estimation of $\boldsymbol{x}_k$ under the condition $\boldsymbol{Z}^k$ based on the linear MMSE (LMMSE) criterion. $\boldsymbol{K}_k$ is the gain matrix and $\boldsymbol{S}_k$ is the covariance matrix of innovation.

$$\overline{z}_k^p = \mathrm{E}^*\left[z_k^p|\boldsymbol{Z}^{k-1}\right] = \mu_1\left[\lambda_1\overline{x}_k,\lambda_1\overline{y}_k,\lambda_1\overline{z}_k\right]^{\mathrm{T}}, \tag{8}$$

$$z_k^p = \begin{bmatrix} r_k^m\cos\theta_k^m\cos\varepsilon_k^m \\ r_k^m\sin\theta_k^m\cos\varepsilon_k^m \\ r_k^m\sin\varepsilon_k^m \end{bmatrix}, \tag{9}$$

$$\boldsymbol{S}_k = \mathrm{cov}\left(z_k^p - \overline{z}_k^p|\boldsymbol{Z}^{k-1}\right), \tag{10}$$

$$\begin{gathered}\boldsymbol{K}_k = \mathrm{cov}\left(\boldsymbol{x}_k - \overline{\boldsymbol{x}}_k, z_k^p - \overline{z}_k^p|\boldsymbol{Z}^{k-1}\right)\boldsymbol{S}_k^{-1} = \mathrm{cov}\left(\widetilde{\boldsymbol{x}}_k,\widetilde{z}_k^p|\boldsymbol{Z}^{k-1}\right)\boldsymbol{S}_k^{-1} = \\ \mu_1\left[\lambda_1\mathrm{cov}(\widetilde{\boldsymbol{x}}_k,\widetilde{x}_k),\lambda_1\mathrm{cov}(\widetilde{\boldsymbol{x}}_k,\widetilde{y}_k),\ \mathrm{cov}(\widetilde{\boldsymbol{x}}_k,\widetilde{z}_k)\right]\boldsymbol{S}_k^{-1},\end{gathered} \tag{11}$$

where $\widetilde{z}_k^p = z_k^p - \overline{z}_k^p$, $\lambda_1 = \mathrm{E}\left(\cos\widetilde{\theta}_k\right) = \mathrm{e}^{-\frac{\sigma_\theta^2}{2}}$ and $\mu_1 = \mathrm{E}(\cos\widetilde{\varepsilon}_k) = \mathrm{e}^{-\frac{\sigma_\varepsilon^2}{2}}$ are constants. $\mathrm{E}(\cdot)$ represents the expection of corresponding elements. The detail expression of the predicted position measurement error covariance matrix $\boldsymbol{S}_k$ was derived in [21], which is not given here for space limitation.

Rewrite the predicted position measurement as

$$\overline{z}_k^p = \begin{bmatrix} \lambda_1\mu_1\overline{x}_k \\ \lambda_1\mu_1\overline{y}_k \\ \mu_1\overline{z}_k \end{bmatrix} = \boldsymbol{\Lambda}_k^{-1}\boldsymbol{H}_k\overline{\boldsymbol{x}}_k \tag{12}$$

where $\boldsymbol{H}_k$ is the measurement matrix, and $\boldsymbol{H}_k = \mathrm{diag}\{[1\ 0], 3\}_{3\times 6}$; $\boldsymbol{\Lambda}_k$ is the bias compensation matrix, which consists of the bias compensation factors λ_1 and μ_1 as

$$\boldsymbol{\Lambda}_k = \begin{bmatrix} \lambda_1^{-1}\mu_1^{-1} & 0 & 0 \\ 0 & \lambda_1^{-1}\mu_1^{-1} & 0 \\ 0 & 0 & \mu_1^{-1} \end{bmatrix}. \tag{13}$$

Substituting (12) into (6), the update state equation can be expressed as a new form as

$$\begin{aligned} \widehat{\boldsymbol{x}}_k^p &= \overline{\boldsymbol{x}}_k + \boldsymbol{K}_k(z_k^p - \overline{z}_k^p) = \\ &\overline{\boldsymbol{x}}_k + \boldsymbol{K}_k(z_k^p - \boldsymbol{\Lambda}_k^{-1}\boldsymbol{H}_k\overline{\boldsymbol{x}}_k) = \\ &\overline{\boldsymbol{x}}_k + \boldsymbol{K}_k\boldsymbol{\Lambda}_k^{-1}(\boldsymbol{\Lambda}_k z_k^p - \boldsymbol{H}_k\overline{\boldsymbol{x}}_k) = \\ &\overline{\boldsymbol{x}}_k + \boldsymbol{C}_k(z_k^{c,p} - \boldsymbol{H}_k\overline{\boldsymbol{x}}_k) \end{aligned} \tag{14}$$

where $\boldsymbol{C}_k = \boldsymbol{K}_k\boldsymbol{\Lambda}_k^{-1}$ is considered as a new form of the Kalman gain.

$$\begin{aligned} \boldsymbol{C}_k = \boldsymbol{K}_k\boldsymbol{\Lambda}_k^{-1} &= \mu_1[\lambda_1\mathrm{cov}(\widetilde{\boldsymbol{x}}_k, \widetilde{x}_k), \lambda_1\mathrm{cov}(\widetilde{\boldsymbol{x}}_k, \widetilde{y}_k), \\ &\mathrm{cov}(\widetilde{\boldsymbol{x}}_k, \widetilde{z}_k)]\cdot\boldsymbol{S}_k^{-1}\boldsymbol{\Lambda}_k^{-1} = [\mathrm{cov}(\widetilde{\boldsymbol{x}}_k, \widetilde{x}_k), \mathrm{cov}(\widetilde{\boldsymbol{x}}_k, \widetilde{y}_k), \\ &\mathrm{cov}(\widetilde{\boldsymbol{x}}_k, \widetilde{z}_k)]\cdot\boldsymbol{\Lambda}_k^{-1}\boldsymbol{S}_k^{-1}\boldsymbol{\Lambda}_k^{-1} \end{aligned} \tag{15}$$

and $\boldsymbol{\Lambda}_k z_k^p$ is denoted as $z_k^{c,p}$.

$$z_k^{c,p} = [x_k^c\ y_k^c\ z_k^c]^{\mathrm{T}} = \begin{bmatrix} \lambda_1^{-1}\mu_1^{-1}r_k^m\cos\theta_k^m\cos\varepsilon_k^m \\ \lambda_1^{-1}\mu_1^{-1}r_k^m\sin\theta_k^m\cos\varepsilon_k^m \\ \mu_1^{-1}r_k^m\sin\varepsilon_k^m \end{bmatrix} \tag{16}$$

From (16), $z_k^{c,p}$ can be considered as a measurement conversion of z_k^p with a multiplicative nature of the bias $\boldsymbol{\Lambda}_k$.

Furthermore, rewrite the covariance in (7) with respect to $\boldsymbol{C}_k$ as

$$\begin{aligned} \boldsymbol{P}_k^p &= \overline{\boldsymbol{P}}_k - \boldsymbol{K}_k\boldsymbol{S}_k\boldsymbol{K}_k^{\mathrm{T}} = \\ &\overline{\boldsymbol{P}}_k - \boldsymbol{K}_k\boldsymbol{\Lambda}_k^{-1}\left[\boldsymbol{\Lambda}_k\boldsymbol{S}_k\boldsymbol{\Lambda}_k^{\mathrm{T}}\right]\left[\boldsymbol{K}_k\boldsymbol{\Lambda}_k^{-1}\right]^{\mathrm{T}} = \\ &\overline{\boldsymbol{P}}_k - \boldsymbol{C}_k\boldsymbol{D}_k\boldsymbol{C}_k^{\mathrm{T}} \end{aligned} \tag{17}$$

where $\boldsymbol{D}_k$ is defined as $\boldsymbol{D}_k = \boldsymbol{\Lambda}_k\boldsymbol{S}_k\boldsymbol{\Lambda}_k^{\mathrm{T}}$, which is considered to be the new innovation covariance. Consider the relationship between the innovation and measurement error covariance in the Kalman filter. We should have

$$\boldsymbol{D}_k = \boldsymbol{H}_k\overline{\boldsymbol{P}}_k\boldsymbol{H}_k^{\mathrm{T}} + \boldsymbol{R}_k^p. \tag{18}$$

Therefore, BLUE is a kind of CMKF, whose converted measurement is $z_k^{c,p}$ and the corresponding covariance $\boldsymbol{R}_k^p$ is

$$\boldsymbol{R}_k^p = \boldsymbol{D}_k - \boldsymbol{H}_k\overline{\boldsymbol{P}}_k\boldsymbol{H}_k^{\mathrm{T}} = \boldsymbol{\Lambda}_k\boldsymbol{S}_k\boldsymbol{\Lambda}_k^{\mathrm{T}} - \boldsymbol{H}_k\overline{\boldsymbol{P}}_k\boldsymbol{H}_k^{\mathrm{T}}. \tag{19}$$

4. DUSQ filtering based on BLUE with additional range rate measurement

Besides the position measurements r_k^m, θ_k^m and ε_k^m, the $\dot{r}_k^m$ measurement is also available in the Doppler radar. The additional Doppler information can be sequentially used to improve the target tracking performance.

4.1 Conventional sequential filtering algorithm

To eliminate the nonlinear influence of the range rate, the pseudo measurement equation is constructed as follows:

$$\xi_k^m = r_k^m\dot{r}_k^m = x_k\dot{x}_k + y_k\dot{y}_k + z_k\dot{z}_k + \widetilde{\xi}_k \tag{20}$$

where $\widetilde{\xi}_k$ is the error of pseudo measurement with the mean $\mathrm{E}\left[\widetilde{\xi}_k | r_k, \dot{r}_k\right] = \rho\sigma_r\sigma_{\dot{r}}$. The de-biased pseudo measurement conversion can be given as

$$\xi_k^c = r_k^m\dot{r}_k^m - \rho\sigma_r\sigma_{\dot{r}} = \xi_k + \widetilde{\xi}_k^c \tag{21}$$

where ξ_k is the true pseudo measurement defined as $\xi_k = r_k\dot{r}_k = x_k\dot{x}_k + y_k\dot{y}_k + z_k\dot{z}_k$, $\widetilde{\xi}_k^c$ is the error of the converted pseudo measurement in the Cartesian coordinates.

The structure of sequential filtering is shown in Fig. 1.

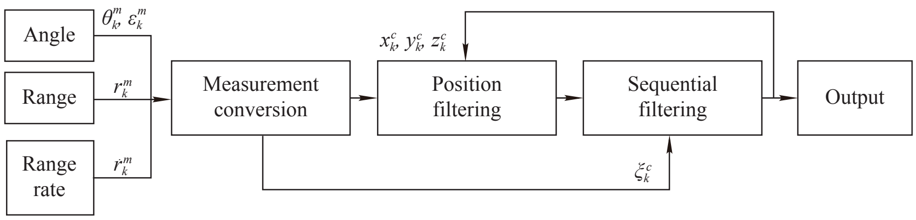

Fig. 1 Structure of conventional sequential filter

In the sequential structure where the position filter based on the converted position measurements (x_k^c, y_k^c and z_k^c) is followed by the filter based on the de-biased pseudo measurement ξ_k^c, both ξ_k^c and the position filter input are related to r_k^m, which leads to the correlation between x_k^c, y_k^c, z_k^c and ξ_k^c.

Because the derivation of the mean and covariance matrix of the converted measurement error is conditioned on the radar measurement [13], the final state estimation is correlated to the measurement and a biased estimate will be obtained.

4.2 DUSQ filtering based on BLUE

To overcome the drawbacks in the conventional sequential filtering algorithm, the statistic characteristics of the converted measurement error is calculated conditioned on the predicted position in the proposed algorithm. As shown in Section 3, BLUE with position measurements can be seen as a kind of CMKF, which is based on the predicted position information of the target. The converted measurement position filter in the conventional sequential algorithm is replaced by the Kalman form of BLUE.

The statistic of the converted pseudo measurement error is also calculated conditioned on the predicted information to avoid the drawbacks calculated based on measurement information. For brevity, we drop the time index k in the predicted information, i.e., let r_t and $\widetilde{r}_t$ stand for $r_{k,t}$ and $\widetilde{r}_{k,t}$. The relationship between the predicted and true values can be expressed as

$$\begin{cases} r_t = r_k + \widetilde{r}_t \\ \dot{r}_t = \dot{r}_k + \widetilde{\dot{r}}_t \\ \theta_t = \theta_k + \widetilde{\theta}_t \\ \varepsilon_t = \varepsilon_k + \widetilde{\varepsilon}_t \end{cases} \tag{22}$$

where r_t, θ_t, ε_t and $\dot{r}_t$ are the predicted range, bearing, elevation and range rate of the target, respectively; $\widetilde{r}_t$, $\widetilde{\theta}_t$, $\widetilde{\varepsilon}_t$ and $\widetilde{\dot{r}}_t$ are the corresponding predicted errors. The measurements can be expressed further as

$$\begin{cases} r_k^m = r_t - \widetilde{r}_t + \widetilde{r}_k \\ \dot{r}_k^m = \dot{r}_t - \widetilde{\dot{r}}_t + \widetilde{\dot{r}}_k \\ \theta_k^m = \theta_t - \widetilde{\theta}_t + \widetilde{\theta}_k \\ \varepsilon_k^m = \varepsilon_t - \widetilde{\varepsilon}_t + \widetilde{\varepsilon}_k \end{cases}. \tag{23}$$

The mean $\boldsymbol{m}_k^c$ and the covariance $\boldsymbol{R}_k^c$ of converted measurement errors are calculated conditioned on the predicted information as

$$\boldsymbol{R}_k^c = \begin{bmatrix} & & & R_k^{x\xi} \\ & \boldsymbol{R}_k^p & & R_k^{y\xi} \\ & & & R_k^{z\xi} \\ R_k^{x\xi} & R_k^{y\xi} & R_k^{z\xi} & R_k^{\xi} \end{bmatrix},$$

$$\boldsymbol{m}_k^c = \mathrm{E}\left\{\left[\widetilde{x}_k^c\ \widetilde{y}_k^c\ \widetilde{z}_k^c\ \widetilde{\xi}_k^c\right]^{\mathrm{T}} \middle| r_t, \dot{r}_t, \theta_t, \varepsilon_t\right\} = \boldsymbol{0}_{4\times1}, \tag{24}$$

$$R_k^{x\xi} = \mathrm{cov}\left[\widetilde{x}_k^c, \widetilde{\xi}_k^c | r_t, \dot{r}_t, \theta_t, \varepsilon_t\right] = \\ \mathrm{e}^{-\frac{\sigma_{\theta_t}^2}{2}} \mathrm{e}^{-\frac{\sigma_{\varepsilon_t}^2}{2}} \cos\theta_t \cos\varepsilon_t \left(\rho\sigma_r\sigma_{\dot{r}} r_t + \sigma_r^2 \dot{r}_t\right), \tag{25}$$

$$R_k^{y\xi} = \mathrm{cov}\left[\widetilde{y}_k^c, \widetilde{\xi}_k^c \middle| r_t, \dot{r}_t, \theta_t, \varepsilon_t\right] = \\ \mathrm{e}^{-\frac{\sigma_{\theta_t}^2}{2}} \mathrm{e}^{-\frac{\sigma_{\varepsilon_t}^2}{2}} \sin\theta_t \cos\varepsilon_t \left(\rho\sigma_r\sigma_{\dot{r}} r_t + \sigma_r^2 \dot{r}_t\right), \tag{26}$$

$$R_k^{z\xi} = \mathrm{cov}[\widetilde{z}_k^c, \widetilde{\xi}_k^c | r_t, \dot{r}_t, \theta_t, \varepsilon_t] = \\ \mathrm{e}^{-\frac{\sigma_{\varepsilon_t}^2}{2}} \sin\varepsilon_t (\rho\sigma_r\sigma_{\dot{r}} r_t + \sigma_r^2 \dot{r}_t), \tag{27}$$

$$R_k^{\xi} = \mathrm{cov}\left[\widetilde{\xi}_k^c \middle| r_t, \dot{r}_t\right] = \\ \left(1 + 2\rho^2\right)\sigma_r^2\sigma_{\dot{r}}^2 + \sigma_r^2\left(\dot{r}_t^2 + \sigma_{\dot{r}_t}^2\right) - (\rho\sigma_r\sigma_{\dot{r}})^2 + \\ 2\rho\sigma_r\sigma_{\dot{r}}\left(r_t\dot{r}_t + \sigma_{r_t}\sigma_{\dot{r}_t}\right) + \sigma_{\dot{r}}^2\left(r_t^2 + \sigma_{r_t}^2\right) \tag{28}$$

where $\widetilde{x}_k^c$, $\widetilde{y}_k^c$, $\widetilde{z}_k^c$ and $\widetilde{\xi}_k^c$ are the converted measurement errors in positions and pseudo measurement; the predicted error variances $\sigma_{r_t}^2$, $\sigma_{\theta_t}^2$, $\sigma_{\varepsilon_t}^2$ and $\sigma_{\dot{r}_t}^2$ can be obtained by Jacobian transformation on the predicted error covariance; the predicted values r_t, θ_t, ε_t and $\dot{r}_t$ can be obtained according to the predicted state. In addition, the position converted measurement error covariance $\boldsymbol{R}_k^p$ can be obtained by (19).

Based on above results, we can use the sequential filter to update the position estimation according to (14) and (17) from the BLUE filter. The sequential filtering process is similar with the conventional one, including the de-correlation between position and pseudo measurements and EKF. The difference is that the converted measurement error covariance matrix $\boldsymbol{R}_k^p$ is replaced by (19), and the remaining items in $\boldsymbol{R}_k^c$ are calculated by (25)–(28). Finally, DUSQ filtering based on the BLUE algorithm is obtained.

Assume the state estimation at $k-1$ is $\widehat{\boldsymbol{x}}_{k-1}$ and the corresponding estimation error covariance is $\boldsymbol{P}_{k-1}$, the DUSQ is used to obtain $\widehat{\boldsymbol{x}}_k$ and $\boldsymbol{P}_k$ according to the following steps.

Step 1 Calculate the predicted state $\overline{\boldsymbol{x}}_k$ and corresponding covariance $\overline{\boldsymbol{P}}_k$ according to (4) and (5), and use the position measurements r_k^m, θ_k^m and ε_k^m of the Doppler radar to obtain the converted position measurement $\boldsymbol{z}_k^{c,p}$ as in (16), the gain of the Kalman filter form of BLUE $\boldsymbol{C}_k$ is obtained by (15), and then the position state estimation $\widehat{\boldsymbol{x}}_k^p$ and $\boldsymbol{P}_k^p$ can be obtained according to (14) and (17).

Step 2 Use r_k^m and $\dot{r}_k^m$ to obtain the de-biased pseudo measurement according to (21) and the corresponding statistical characteristics from (24)–(28).

Step 3 De-correlate between the position and pseudo measurements, where the Cholesky factorization [13] is applied to obtaining the de-correlated pseudo measurement.

Step 4 Use the de-correlated pseudo measurement and position state estimation to filter sequentially, where the nonlinear filtering algorithm is similar with the process in the conventional sequential filter. The final state estimation $\widehat{\boldsymbol{x}}_k$ and the corresponding error covariance $\boldsymbol{P}_k$ are obtained.

In summary, the structure of the proposed filter DUSQ is shown in Fig. 2, where SQ stands for sequential. The original radar measurements, i.e., range, bearing, elevation and range rate are divided into two parts to be processed separately. More specifically, the angle and range measurements are input to the BLUE filter, which is considered to be the Kalman filter combined with a position measurement conversion based on the predicted position. On the other hand, the range and range rate measurements are transformed to the pseudo converted measurement by the Doppler conversion module and the EKF is used to process the pseudo converted measurement sequentially. The state estimation is obtained by the sequential filter finally.

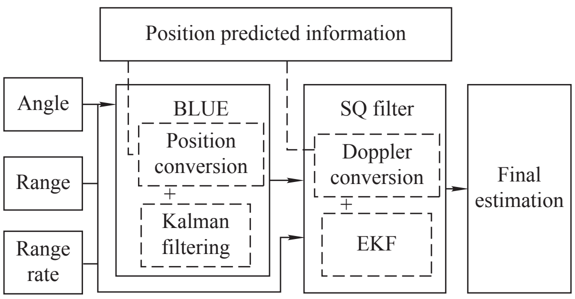

Fig. 2 Structure of DUSQ filter

5. Extension to the maneuvering target tracking case

In practice, most targets have maneuvering characteristics. The IMM algorithm is an effective maneuvering target tracking method and it is easy to combine with various filters due to the structure of it [25]. Therefore, the proposed algorithm DUSQ is extended to the maneuvering target tracking case. More specifically, DUSQ is fused within the IMM framework to obtain the DUSQ-IMM algorithm, where each sub-model consists of a DUSQ filter and the frame of DUSQ-IMM is shown in Fig. 3. The filtering steps are shown as below.

(i) Estimation interaction

Assume that the position estimated state $\widehat{\boldsymbol{x}}_{k-1}^{i,p}$ and the corresponding covariance $\boldsymbol{P}_{k-1}^{i,p}$ of model i at time $k-1$ are known, the interaction state estimation and the error covariance of each filter can be obtained as

$$\widehat{\boldsymbol{x}}_{k-1}^{0,j} = \sum_{i=1}^{N} \widehat{\boldsymbol{x}}_{k-1}^{i,p} \mu_{k-1}^{(i|j)}, \tag{29}$$

$$\boldsymbol{P}_{k-1}^{0,j} = \sum_{i=1}^{N} \mu_{k-1}^{(i|j)} \Big[\boldsymbol{P}_{k-1}^{i,p} + \left(\widehat{\boldsymbol{x}}_{k-1}^{i,p} - \widehat{\boldsymbol{x}}_{k-1}^{0,j}\right)\left(\widehat{\boldsymbol{x}}_{k-1}^{i,p} - \widehat{\boldsymbol{x}}_{k-1}^{0,j}\right)^{\mathrm{T}} \Big], \tag{30}$$

where N is the total number of models, and $\mu_{k-1}^{(i|j)}$ is the probability of model i at time $k-1$, under the condition of model j at time k.

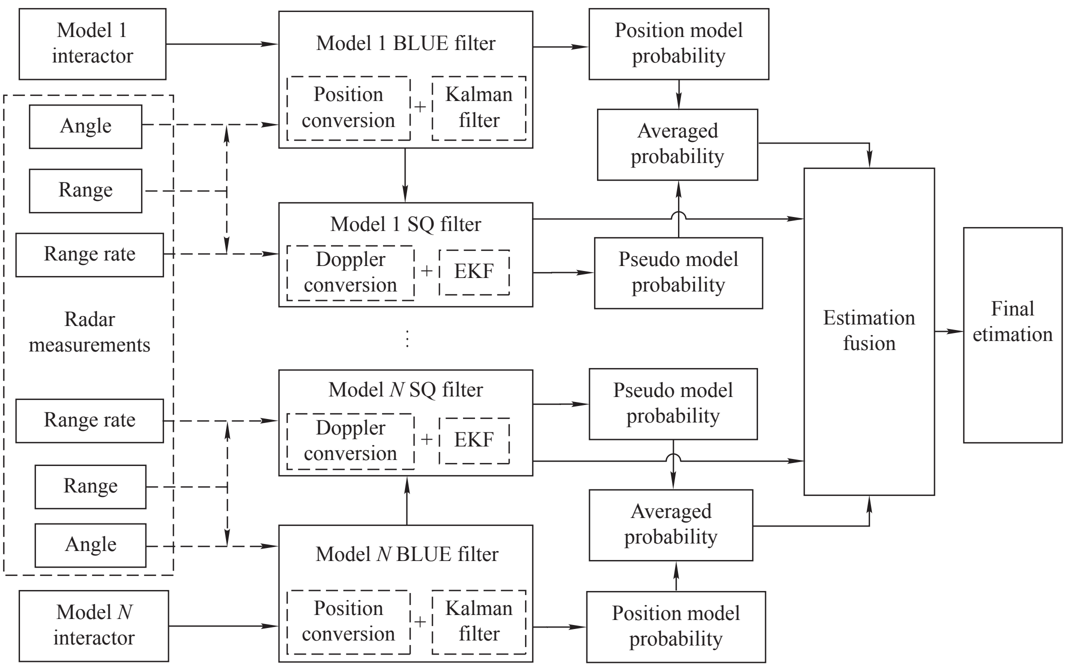

Fig. 3 Frame of DUSQ-IMM algorithm

(ii) DUSQ of each model

Based on the interaction results and the measurements, perform DUSQ for each model to obtain $\widehat{\boldsymbol{x}}_k^j$ and $\boldsymbol{P}_k^j$ $(j = 1, 2, \cdots, N)$.

(iii) Model probability update

In order to improve the accuracy of updated model probabilities, the model probabilities updated from BLUE and the sequential filter are fused to obtain the updated model probability.

$$\mu_k^j = w_k^{j,p}\mu_k^{j,p} + w_k^{j,\xi}\mu_k^{j,\xi} \tag{31}$$

where $w_k^{j,p}$ and $w_k^{j,\xi}$ are the corresponding weight coefficients, $\mu_k^{j,p}$ and $\mu_k^{j,\xi}$ are the model probabilities from position and pseudo measurement filters as

$$\begin{cases} \mu_k^{j,p} = L_k^{j,p} \dfrac{\bar{c}_j^p}{c^p} \\ \mu_k^{j,\xi} = L_k^{j,\xi} \dfrac{\bar{c}_j^\xi}{c^\xi} \end{cases} \tag{32}$$

where

$$\begin{cases} \bar{c}_j^p = \displaystyle\sum_{i=1}^N \pi_{ij}\mu_{k-1}^{i,p} \\ \bar{c}_j^\xi = \displaystyle\sum_{i=1}^N \pi_{ij}\mu_{k-1}^{i,\xi} \end{cases}, \tag{33}$$

$$\begin{cases} c^p = \displaystyle\sum_{j=1}^N L_k^{j,p}\bar{c}_j^p, \\ c^\xi = \displaystyle\sum_{j=1}^N L_k^{j,\xi}\bar{c}_j^\xi \end{cases}. \tag{34}$$

π_{ij} is the transition probability of the system from model i to model j. The likelihood function of each filter is calculated as

$$\begin{cases} L_k^{j,p} = \left|2\pi \boldsymbol{S}_k^{j,p}\right|^{-\frac{1}{2}} \cdot \exp\left\{-\dfrac{1}{2}\left(\boldsymbol{e}_k^{j,p}\right)^{\mathrm{T}}\left(\boldsymbol{S}_k^{j,p}\right)^{-1}\boldsymbol{e}_k^{j,p}\right\} \\ L_k^{j,\xi} = \left|2\pi \boldsymbol{S}_k^{j,\xi}\right|^{-\frac{1}{2}} \cdot \exp\left\{-\dfrac{1}{2}\left(\boldsymbol{e}_k^{j,\xi}\right)^{\mathrm{T}}\left(\boldsymbol{S}_k^{j,\xi}\right)^{-1}\boldsymbol{e}_k^{j,\xi}\right\} \end{cases} \tag{35}$$

where $\boldsymbol{e}_k^{j,p}$ is the residual from the BLUE filter with the corresponding covariance $\boldsymbol{S}_k^{j,p}$, and $\boldsymbol{e}_k^{j,\xi}$ is the sequential residual with the corresponding covariance $\boldsymbol{S}_k^{j,\xi}$.

(iv) Final estimation

The filtering results are weighted by the updated probabilities to obtain the final estimation as

$$\widehat{\boldsymbol{x}}_k = \sum_{j=1}^N \widehat{\boldsymbol{x}}_k^j \mu_k^j, \tag{36}$$

$$\boldsymbol{P}_k = \sum_{j=1}^N \mu_k^j\left(\boldsymbol{P}_k^j + \left[\widehat{\boldsymbol{x}}_k^j - \widehat{\boldsymbol{x}}_k\right]\left[\widehat{\boldsymbol{x}}_k^j - \widehat{\boldsymbol{x}}_k\right]^{\mathrm{T}}\right). \tag{37}$$

6. Simulation

Assume the target is initially located at (3 000 m, 6 000 m, 100 m), with the velocity of (100 m/s, 30 m/s, 2 m/s). It performs nearly constant velocity (NCV) motion during the whole tracking period and the sampling interval of the Doppler radar is 1 s. The radar measurements include the range, bearing, elevation angle and Doppler measurements with zero-mean Gaussian white measurement noises and the standard deviations of them are σ_r, σ_θ, σ_ε and $\sigma_{\dot{r}}$ respectively, and the correlation coefficient between range and range rate is denoted as ρ. The process noise is assumed to be zero-mean Gaussian white with the standard deviation of $q = 0.2$ m/s^2. The number of Monte Carlo runs is 200.

DUSQ is used to realize target tracking. Meanwhile, the conventional SELF in [13], the SFCMKF in [15] and the BLUE with Doppler measurement approach (BLUESF) in [23] are simulated. In order to better verify the performance of the proposed algorithm, Table 1 provides the measurement parameters setting for each case [15]. The performances of the algorithms are compared in terms of the position and velocity root mean squared errors (RMSEs) and non-credibility index (NCI). The RMSE is generally used to evaluate the tracking accuracy of the algorithm and the NCI [30] is the metric used to evaluate the consistency between the estimated state error and the corresponding covariance. The smaller the values of RMSE and NCI, the better the tracking performance of the algorithm.

Table 1 Measurement parameters in different cases [15]

Parameter	1	2	3	4	5	6	7
σ_r/m	50	50	100	100	150	150	150
σ_θ/(°)	0.1	0.1	0.2	0.2	0.5	0.5	0.5
σ_ε/(°)	0.1	0.1	0.2	0.2	0.5	0.5	0.5
$\sigma_{\dot{r}}$/(m/s)	0.1	0.1	0.1	0.1	0.1	0.9	1.5
ρ	0.9	0	0	–0.9	0	0	0

The RMSE of comparison results under different measurement parameter settings are shown in Figs. 4–10. Firstly, the proposed DUSQ has the best performance among all algorithms, since its unbiased measurement conversion and the statistical characteristic of the converted measurement error are deduced based on the predicted position information. In SEKF and SFCMKF, the measurement conversion is a de-biased one and the statistical characteristic of the converted measurement error is deduced based on the measurement. Therefore, the tracking performance is not as good as DUSQ. BLUESF and SFCMKF fall into the category of the SF algorithm, which indicates that they require a great deal of time to converge for the pseudo state estimation, especially in large position measurements errors cases, see Figs. 8–10.

Secondly, in order to evaluate the influence of the correlation coefficient ρ, the RMSE comparisons with $\rho = 0.9$, $\rho = 0$, and $\rho = -0.9$, $\rho = 0$ in different position measurements errors are shown in Fig. 4, Fig. 5, Fig. 6 and Fig. 7. It can be seen that the performances of these algorithms are not influenced by the correlation between range and range rate measurements.

Thirdly, to evaluate the influence of position measurements accuracy on estimation, ρ and $\sigma_{\dot{r}}$ are fixed, and the RMSE comparisons under different position measurement errors are given in Fig. 5, Fig. 6 and Fig. 8. It can be seen that DUSQ has the best performance and the advantage of it is more obvious as the position measurement errors increase.

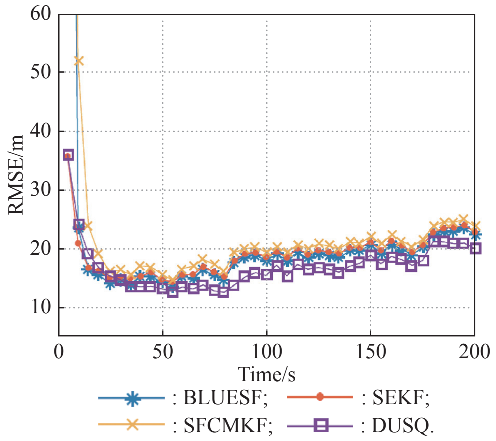

Fig. 4 Position RMSE of Case 1

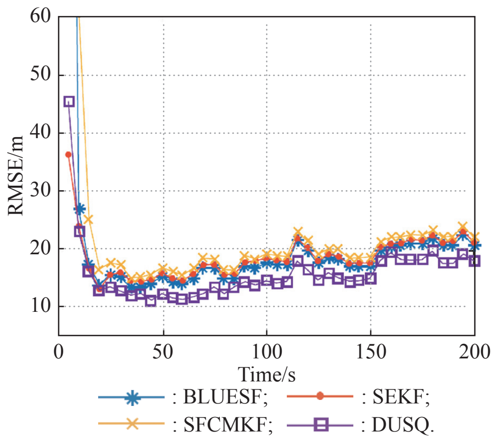

Fig. 5 Position RMSE of Case 2

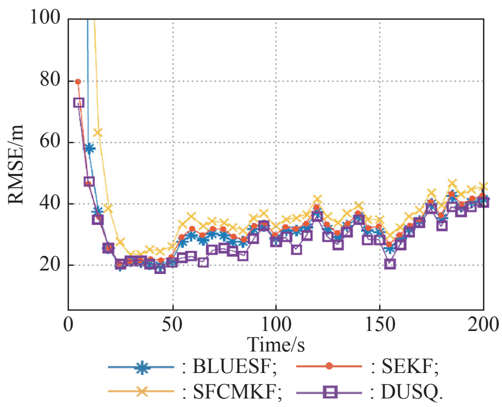

Fig. 6 Position RMSE of Case 3

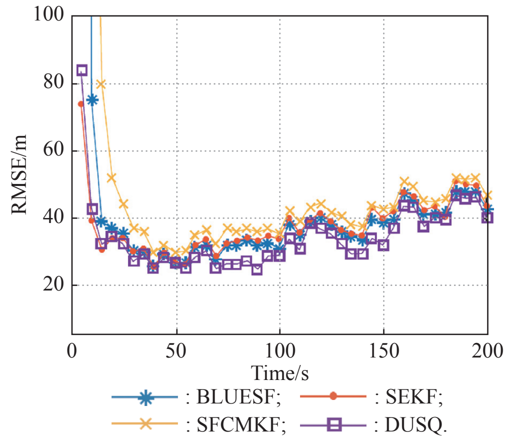

Fig. 7 Position RMSE of Case 4

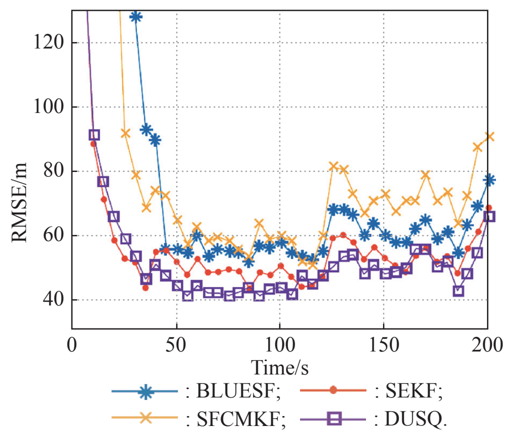

Fig. 8 Position RMSE of Case 5

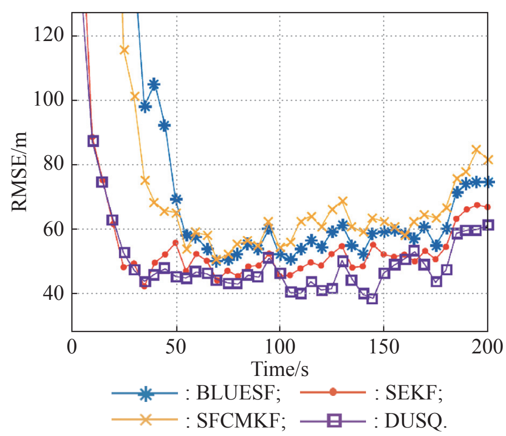

Fig. 9 Position RMSE of Case 6

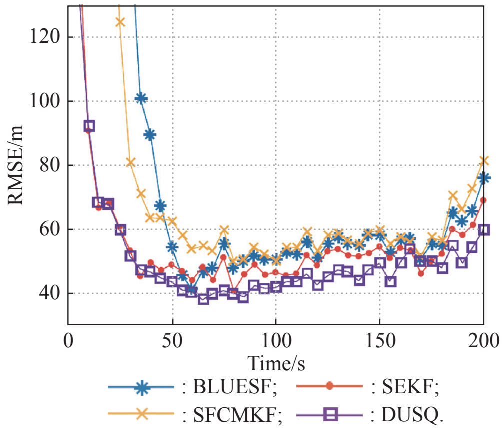

Fig. 10 Position RMSE of Case 7

Finally, the standard deviation of the Doppler measurement error $\sigma_{\dot{r}}$ is varied to investigate the influence of it on the estimation performance. Figs. 8–10 show the RMSE comparisons when $\sigma_{\dot{r}}$ is 0.1 m/s, 0.9 m/s and 1.5 m/s, respectively. It can be seen that DUSQ has the best performance and the superiority of it is more obvious as the Doppler measurement error decreases.

The NCI comparison result with $\sigma_r = 150$ m, $\sigma_\theta = \sigma_\varepsilon = 0.5°$, $\sigma_{\dot{r}} = 1.5$ m/s and $\rho = 0$ is shown in Fig. 11, and the results in other cases are similar, which are not given repeatedly. It can be seen that DUSQ has the smallest NCI in this case, which indicates that DUSQ is noticeably superior to other algorithms in terms of consistency. Furthermore, the NCIs of SEKF and SFCMKF are very close due to the measurement conversion based on radar measurements, the NCIs of BLUESF and DUSQ are similar and lower than the other two NCIs, because the BLUE algorithm is utilized in BLUESF and DUSQ, and the introduction of the BLUE can avoid the drawback of measurement conversion based on measurements.

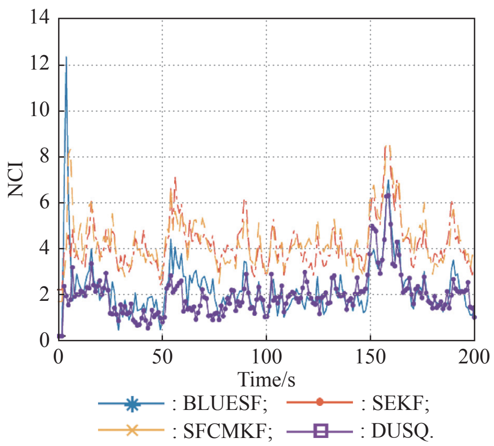

Fig. 11 Comparison of NCIs with different algorithms

Besides tracking accuracy of algorithms, computation burden is another important performance index. Simulations are made using Matlab R2016b on a 2.40 GHz Intel core i5-2430 PC for 100 iterations. Results are shown in Fig. 12. It can be seen that the DUSQ algorithm is achieved without increasing computation burden significantly, while the computation burden of the other two SF-type (BLUESF and SFCMKF) algorithms is large.

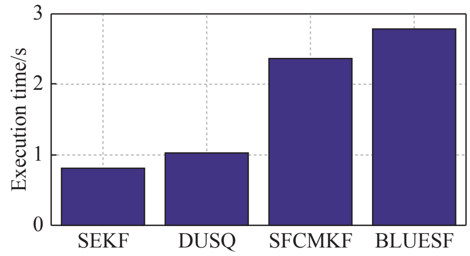

Fig. 12 Computation cost of 100 iterations

In order to verify the effectiveness of DUSQ-IMM in the maneuvering case, the simulation scene in [27] is set here: a target starts at (–2 000 m, 1 000 m, 100 m) and moves with velocities of (20 m/s, 0 m/s, 0 m/s) for 20 s, then acceleration along the x-axis increases to 5 m/s^2 within 15 s. After constant acceleration (CA) motion for 10 s, the acceleration along the x-axis decreases to 0 m/s^2 within 15 s, then the target resumes constant velocity (CV) motion. The acceleration turbulences along each axis are 0.1 m/s^2. The measurement accuracy is $\sigma_r = 10$ m for range, $\sigma_\theta = \sigma_\varepsilon = 0.1°$ for bearing and elevation, and $\sigma_{\dot{r}} = 0.1$ m/s for range rate. Simulation time span is 130 s. In DUSQ-IMM, the initial probability of each model is set to be 0.5, and the probability transfer matrix is $\begin{bmatrix} 0.9 & 0.1 \\ 0.1 & 0.9 \end{bmatrix}$. The weight of the position and pseudo measurement model probability are set to be 0.5. The position and velocity RMSEs of DUSQ-IMM are shown in Fig. 13 and Fig. 14. It can be seen that DUSQ-IMM can realize effective target tracking in this scene.

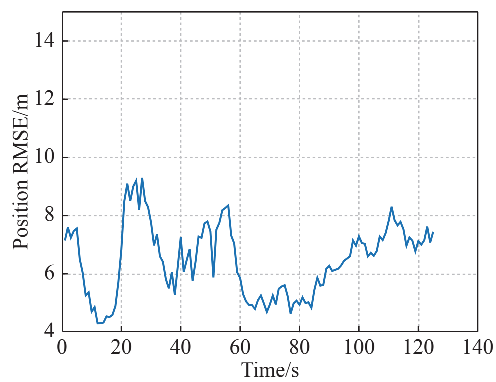

Fig. 13 Position RMSE of maneuvering case with σ_r=10 m, $\sigma_\theta = \sigma_\varepsilon = 0.1°$, $\sigma_{\dot{r}} = 0.1$ m/s and $\rho = 0$

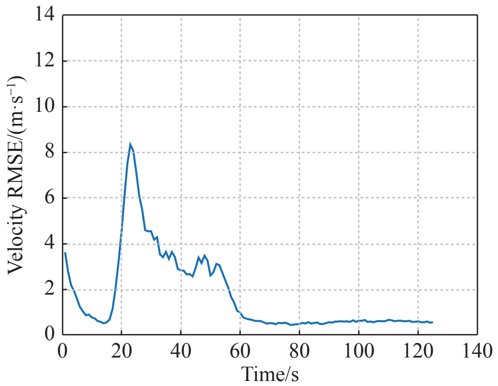

Fig. 14 Velocity RMSE of maneuvering case with $\sigma_r = 10$ m, $\sigma_\theta = \sigma_\varepsilon = 0.1°$, $\sigma_{\dot{r}} = 0.1$ m/s and $\rho = 0$

The proposed algorithm is compared with MIE-BLUE in [27] in terms of averaged RMSE and the results are shown in Table 2. It can be seen that the averaged RMSE of DUSQ-IMM is significantly lower than the results of the algorithm proposed in [27]. The reason is that the Doppler measurement is utilized in DUSQ-IMM and the tracking accuracy can be greatly improved by this additional Doppler information. The model probabilities in DUSQ-IMM are updated from the Kalman filter form of the BLUE and the sequential filter, so the accuracy of the updated model probability is higher. The updated model probabilities are shown in Fig. 15, where NCA stands for nearly constant acceleration.

Table 2 Comparison of averaged RMSEs

Parameter	DUSQ-IMM	MIE-BLUE [27]
Position/m	6.704 8	7.40
Velocity/(m/s)	1.894 1	3.60

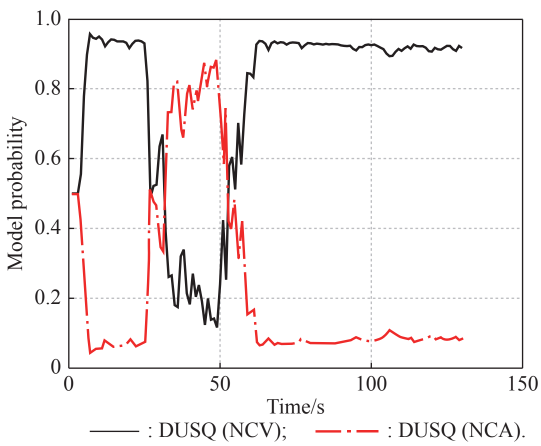

Fig. 15 Model probability

The model probability of CV in DUSQ-IMM is larger than that of CA in the absence of the maneuver, when the target maneuvering and the model probability of CA can increase immediately to match the target motion mode. Consequently, it can accurately estimate the target acceleration. Therefore, the proposed approach DUSQ-IMM can realize effective maneuvering target tracking.

7. Conclusions

For target tracking in the Doppler radar, a new tracking algorithm named DUSQ is presented. In this approach, the position and pseudo measurements are sequentially processed, where the position measurement filter BLUE is considered as a kind of CMKF with special converted measurements and error covariance, and the sequential filter based on the pseudo measurement is used to handle the Doppler measurement further. The involved pseudo measurement conversion is based on the predicted information to avoid the drawback based on the measurement information. Through simulation results, the proposed algorithm is noticeably superior to other methods and its extended algorithm DUSQ-IMM can realize maneuvering target tracking. Therefore, DUSQ and its extension are effective algorithms for Doppler radar target tracking.

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