



Supplementary materials for

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1 The target-tracking algorithm

The purpose of moving-target tracking is to estimate the target state at each time step. For target n , the expectation and covariance matrix of its state estimation at time step k are denoted as

$$\hat{\mathbf{X}}_{k|k}^n = \left[\hat{x}_{k|k}^n, \hat{y}_{k|k}^n, \hat{v}_{k|k}^n, \hat{w}_{k|k}^n \right]^T \text{ and } \mathbf{P}_{k|k}^n, \text{ respectively.}$$

For the off-road target, whose motion is not influenced by road constraints and for which the motion model set $\boldsymbol{\eta}_{\text{model},k}^n$ is fixed, we apply the interacting multiple model (IMM) and cubature Kalman filter (CKF) algorithm to track it (Xu et al., 2019).

For the on-road target, the motion model is related to the road segment where it is located. Therefore, its motion model set $\boldsymbol{\eta}_{\text{model},k}^n$ is time-varying and cannot be tracked by the IMM algorithm. To solve this problem, we introduce the variable-structure interacting multiple model (VS-IMM) algorithm (Kirubarajan and Bar-Shalom, 2003; Yu, et al., 2016), in which the model set can be updated adaptively and the target state is then estimated based on the IMM algorithm. As explained in Section 4.2, the motion model of the on-road target at each time step is determined by the road segment where it is located, and the motion model is updated when the road segment has changed. Hence, we designed an updated motion-model-set strategy based on target state.

First, we judge whether the target is located at an intersection based on Eq. (S1).

$$\left[x_{\text{inter}} - \hat{x}_{k-1|k-1}^n, y_{\text{inter}} - \hat{y}_{k-1|k-1}^n \right] \widehat{\mathbf{P}}_{k-1|k-1}^n \begin{bmatrix} x_{\text{inter}} - \hat{x}_{k-1|k-1}^n \\ y_{\text{inter}} - \hat{y}_{k-1|k-1}^n \end{bmatrix} \leq \chi \quad (\text{S1})$$

where $(x_{\text{inter}}, y_{\text{inter}})$ is the coordinate of intersection, $\widehat{\mathbf{P}}_{k-1|k-1}^n$ is the position component of $\mathbf{P}_{k-1|k-1}^n$, and χ is the gate threshold of Mahalanobis distance.

Then, the motion-model set is updated in the following three cases, depending on the location of the target. Fig. S1(a) to (c) shows diagrams of the three cases.

Case 1. The road segment where target n is located at $k-1$ is the same as its location at $k-2$.

This case indicates that the model set remains unchanged, that is, $\boldsymbol{\eta}_{\text{model},k-1}^n = \boldsymbol{\eta}_{\text{model},k-2}^n$.

Case2. The road segment where target n is located at $k-1$ is different from its location at $k-2$.

In this case, the model set should be updated, all the models are deleted from $\boldsymbol{\eta}_{\text{model},k-2}^n$, and the model corresponding to the current road segment is added in $\boldsymbol{\eta}_{\text{model},k-1}^n$.

Case 3. Target n is located at the intersection of multiple road segments.

In this case, the model set should be updated, all the models are deleted from $\boldsymbol{\eta}_{\text{model},k-2}^n$, and the models

corresponding to all road segments connected to the intersection are added in $\eta_{\text{model},k-1}^n$.

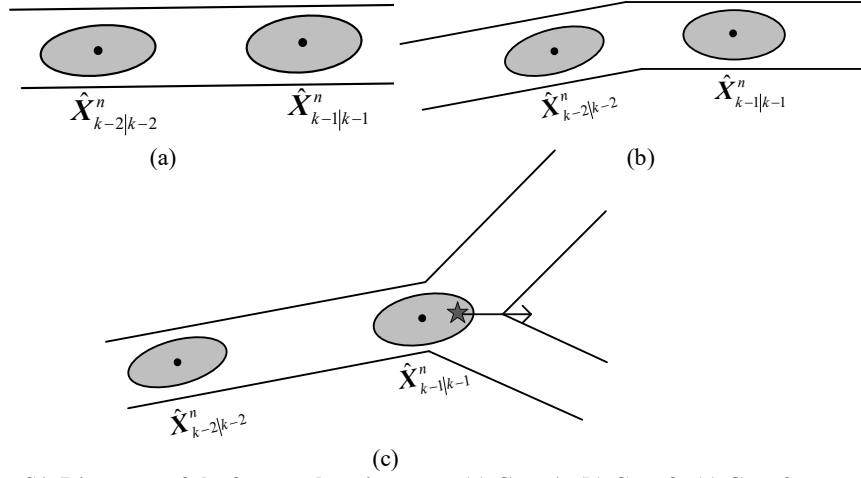


Fig. S1 Diagrams of the 3 target location cases (a) Case 1; (b) Case 2; (c) Case 3

After updating the model set, the IMM algorithm can be used to estimate the on-road target state in the same way as the off-road target state.

However, because of the presence of the Doppler blind area, the measurement of the target may not be obtained by the multi-sensor system. At this point, the measurement update cannot be performed in the filter, and the target state can only be predicted through the motion model, that is

$$\begin{cases} \hat{X}_{k|k}^n = \sum_{i=1}^{\eta_{\text{total}}} \mu_k^i \hat{X}_{k|k}^{i,n} \\ \mathbf{P}_{k|k}^n = \sum_{i=1}^{\eta_{\text{total}}} \left\{ \mu_k^i \left[\left(\hat{X}_{k|k}^n - \hat{X}_{k|k}^{i,n} \right) \left(\hat{X}_{k|k}^n - \hat{X}_{k|k}^{i,n} \right)^{\text{T}} + \mathbf{P}_{k|k}^{i,n} \right] \right\} \end{cases} \quad (\text{S2})$$

with

$$\begin{cases} \hat{X}_{k|k}^{i,n} = \tilde{X}_{k|k-1}^{i,n} = \mathbf{F}_{\eta_k=i}^n \hat{X}_{k-1|k-1}^{i,n} \\ \mathbf{P}_{k|k}^{i,n} = \mathbf{P}_{k|k-1}^{i,n} = \mathbf{F}_{\eta_k=i}^n \mathbf{P}_{k-1|k-1}^{i,n} \left(\mathbf{F}_{\eta_k=i}^n \right)^{\text{T}} + \mathbf{\Gamma}_i^n \mathbf{Q}_{\eta_k=i} \left(\mathbf{\Gamma}_{\eta_k=i}^n \right)^{\text{T}} \end{cases} \quad (\text{S3})$$

where η_{total} is the total number of motion models, μ_k^i is the probability of model i at k , $\left(\hat{X}_{k|k}^{i,n}, \mathbf{P}_{k|k}^{i,n} \right)$ is the state estimation under model i at k , and $\left(\tilde{X}_{k|k-1}^{i,n}, \mathbf{P}_{k|k-1}^{i,n} \right)$ is the corresponding state prediction.

2 The PCRLB

The PCRLB is also the inverse of the corresponding Fisher information matrix. According to Song et al. (2019), the PCRLB of target n satisfies the following equation.

$$\mathbb{E} \left\{ \left[\hat{X}_{k|k}^n - \mathbf{X}_k^n \right] \left[\hat{X}_{k|k}^n - \mathbf{X}_k^n \right]^{\text{T}} \right\} \geq \mathbf{PCRLB}_k^n = \left(\mathbf{Fisher}_k^n \right)^{-1} \quad (\text{S4})$$

where \mathbf{PCRLB}_k^n and \mathbf{Fisher}_k^n are the PCRLB and Fisher information matrix of n at k , respectively.

Assuming that sensor m is activated to track target n at k , \mathbf{Fisher}_k^n can be obtained by recursion, that is

$$\mathbf{Fisher}_k^n = \mathbf{D}^{22} \left(\mathbf{X}_{k-1}^n \right) - \mathbf{D}^{21} \left(\mathbf{X}_{k-1}^n \right) \left[\mathbf{Fisher}_{k-1}^n + \mathbf{D}^{11} \left(\mathbf{X}_{k-1}^n \right) \right]^{-1} \mathbf{D}^{12} \left(\mathbf{X}_{k-1}^n \right) + \mathbf{G}_k^n \quad (\text{S5})$$

with

$$\begin{cases} \mathbf{D}^{11}(\mathbf{X}_{k-1}^n) = \mathbb{E}\left[-\Delta_{\mathbf{X}_{k-1}^n} \log p(\mathbf{X}_k^n | \mathbf{X}_{k-1}^n)\right] \\ \mathbf{D}^{12}(\mathbf{X}_{k-1}^n) = \mathbb{E}\left[-\Delta_{\mathbf{X}_{k-1}^n} \log p(\mathbf{X}_k^n | \mathbf{X}_{k-1}^n)\right] \\ \mathbf{D}^{21}(\mathbf{X}_{k-1}^n) = \mathbb{E}\left[-\Delta_{\mathbf{X}_k^n} \log p(\mathbf{X}_k^n | \mathbf{X}_{k-1}^n)\right] \\ \mathbf{D}^{22}(\mathbf{X}_{k-1}^n) = \mathbb{E}\left[-\Delta_{\mathbf{X}_k^n} \log p(\mathbf{X}_k^n | \mathbf{X}_{k-1}^n)\right] \\ \mathbf{G}_k^n = \mathbb{E}\left[-\Delta_{\mathbf{X}_k^n} \log p(\mathbf{Z}_k^{m,n} | \mathbf{X}_k^n)\right] \end{cases} \quad (\text{S6})$$

where symbol Δ indicates the second-order partial derivatives, and \mathbf{G}_k^n is the information gain obtained by sensor measurement.

For the Gaussian systems, Eq. (S6) can be written as

$$\begin{cases} \mathbf{D}^{11}(\mathbf{X}_{k-1}^n) = (\mathbf{F}_{\eta_k}^n)^\top (\mathbf{Q}_{\eta_k}^n)^{-1} \mathbf{F}_{\eta_k}^n \\ \mathbf{D}^{12}(\mathbf{X}_{k-1}^n) = [\mathbf{D}^{21}(\mathbf{X}_{k-1}^n)]^\top = -(\mathbf{F}_{\eta_k}^n)^\top (\mathbf{Q}_{\eta_k}^n)^{-1} \\ \mathbf{D}^{22}(\mathbf{X}_{k-1}^n) = (\mathbf{Q}_{\eta_k}^n)^{-1} \\ \mathbf{G}_k^n = \rho(\mathbf{J}_k^{m,n})^\top (\mathbf{O}^m)^{-1} (\mathbf{J}_k^{m,n}) \end{cases} \quad (\text{S7})$$

where $\mathbf{J}_k^{m,n}$ is the Jacobian matrix of $\mathbf{h}^m(\mathbf{X}_k^n)$ mentioned in Eq. (22) and \mathbf{O}^m is the measurement-error matrix of sensor m . Note that the actual motion model of target n cannot be obtained in sensor scheduling, so we use the model with the maximum probability in the model set $\boldsymbol{\eta}_{\text{model},k}^n$ as the actual motion model, that is

$$\eta_k = \arg \max_{i=1,2,\dots,\eta_{\text{total}}} \mu_k^i \quad (\text{Xu et al., 2019}).$$

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