Method:

1. Initialize: $\hat{\mathbf{y}}_0 = \widehat{\left[\begin{smallmatrix}\bar{\mathbf{x}}_0\\ \hat{\mathbf{x}}_0\end{smallmatrix}\right]} = \mathbf{0}_{2n\times 1},\ R_0 = \mathrm{Var}\left[\begin{smallmatrix}\bar{\mathbf{x}}_0\\ \hat{\mathbf{x}}_0\end{smallmatrix}\right] = \left[\begin{smallmatrix}P_0 & 0\\ 0 & 0\end{smallmatrix}\right]_{2n\times 2n}$.

2. Propagate: $\hat{\mathbf{y}}_t = F_t\hat{\mathbf{y}}_{t-1},\ R_t = F_t R_{t-1} F_t^T + G_t Q_t G_t^T,\ 0 < t \leq \ell$,

   where $F_t = \begin{bmatrix} A_t & B_t L_t \\ K_t H_t A_t & A_t + B_t L_t - K_t H_t A_t \end{bmatrix}$, $G_t = \begin{bmatrix} V_t & 0 \\ K_t H_t V_t & K_t W_t \end{bmatrix}$, and $Q_t = \begin{bmatrix} M_t & 0 \\ 0 & N_t \end{bmatrix}$.

3. Truncate:

   (a) Determine the set of all obstacles in the workspace that potentially intersect the distribution $\mathcal{N}[\mathbf{p}_t, \Sigma_t]$, where the vector $\mathbf{p}_t \in \mathbb{R}^s$ comprises of the corresponding spatial dimensions of the state vector $\mathbf{y}_t = \hat{\mathbf{y}}_t + \left[\begin{smallmatrix}\mathbf{x}_t^\star\\ \mathbf{x}_t^\star\end{smallmatrix}\right]$, and Σ_t is the marginal distribution over the spatial dimensions of the distribution $\mathcal{N}[\hat{\mathbf{y}}_t, R_t]$.

   (b) Each obstacle in the potentially intersecting set, $\mathcal{O}_i, i = 0, \ldots, k$, defines a feasible half-space defined by the tuple $(\mathbf{a}_i, b_i)$, where $\mathbf{a}_i \in \mathbb{R}^s$ is a unit vector normal to the obstacle defined such that $\mathbf{a}_i \mathbf{p}_t \leq b_i$.

   (c) Truncate the joint distribution $\mathcal{N}[\mathbf{y}_t, R_t]$ against the hyperplane $(\tilde{\mathbf{a}}_i, b_i)$, where $\tilde{\mathbf{a}}_i = [\mathbf{a}_i, 0, \ldots, 0]^T$ is a hyperplane in $\mathbb{R}^{2n}$ that is degenerate in all dimensions except the spatial dimensions.

   Applying an affine transformation $\mathbf{y}'_t = \tilde{\mathbf{a}}_i^T \mathbf{y}_t$ transforms the distribution $\mathcal{N}[\mathbf{y}_t, R_t]$ to a one-dimensional Gaussian distribution $\mathcal{N}[\tilde{\mathbf{a}}_i^T \mathbf{y}_t, \tilde{\mathbf{a}}_i^T R_t \tilde{\mathbf{a}}_i]$ along an axis that is normal to the hyperplane $(\tilde{\mathbf{a}}_i, b_i)$. The problem now simplifies to truncating the one-dimensional Gaussian distribution at a specified upper bound given by b_i, which is well-known from standard literature. Let μ and σ^2 be the truncated mean and variance of the transformed distribution.

   The truncated mean of the original distribution are then given by: $\tilde{\mathbf{y}}_t = \mathbf{y}_t + \sum_{i=0}^{k} \frac{R_t \tilde{\mathbf{a}}_i}{\tilde{\mathbf{a}}_i^T R_t \tilde{\mathbf{a}}_i}(\mu - \tilde{\mathbf{a}}_i^T \mathbf{y}_t)$ and the truncated variance is given by: $\tilde{R}_t = R_t + \sum_{i=0}^{k} \frac{R_t \tilde{\mathbf{a}}_i}{\tilde{\mathbf{a}}_i^T R_t \tilde{\mathbf{a}}_i}(\sigma^2 - \tilde{\mathbf{a}}_i^T \mathbf{y}_t \tilde{\mathbf{a}}_i)\frac{\tilde{\mathbf{a}}_i^T R_t^T}{\tilde{\mathbf{a}}_i^T R_t \tilde{\mathbf{a}}_i}$. The term $\frac{R_t \tilde{\mathbf{a}}_i}{\tilde{\mathbf{a}}_i^T R_t \tilde{\mathbf{a}}_i}$ gives the multiplicative *gain* (similar to the gain term in the Kalman filter measurement update equations) that scales the correction to be applied to the mean $\mathbf{y}_t$ and the variance R_t of the original distribution.

   (d) The mean of the joint distribution is now given by: $\hat{\mathbf{y}}_t = (\tilde{\mathbf{y}}_t - \left[\begin{smallmatrix}\mathbf{x}_t^\star\\ \mathbf{x}_t^\star\end{smallmatrix}\right])$ and the variance given by: $R_t = \tilde{R}_t$.

4. Repeat steps (2) and (3) till the end of the plan.