Cooperative mmWave PHD-SLAM with Moving Scatterers

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Abstract—Using the multiple-model (MM) probability hypothesis density (PHD) filter, millimeter wave (mmWave) radio simultaneous localization and mapping (SLAM) in vehicular scenarios is susceptible to movements of objects, in particular vehicles driving in parallel with the ego vehicle. We propose and evaluate two countermeasures to track vehicle scatterers (VSs) in mmWave radio MM-PHD-SLAM. First, locally at each vehicle, we generate and treat the VS map PHD in the context of Bayesian recursion, and modify vehicle state correction with the VS map PHD. Second, in the global map fusion process at the base station, we average the VS map PHD and upload it with self-vehicle posterior density, compute fusion weights, and prune the target with low Gaussian weight in the context of arithmetic average-based map fusion. From simulation results, the proposed cooperative mmWave radio MM-PHD-SLAM filter is shown to outperform the previous filter in VS scenarios.

I. INTRODUCTION

In millimeter wave (mmWave) signals, it is possible to obtain highly resolvable channel parameters in time and angular domains [1], enabling accurate mapping of landmarks. Therefore, a variety of radio simultaneous localization and mapping (SLAM) works have been recently developed [2]–[4]. A single type of static landmark was considered in [2], [3]. However, since radio environments contain different types of objects (small scattering objects, large reflecting objects, and moving objects), with different state definitions, multiple model (MM) filters, such as the probability hypothesis density (PHD) filter have been developed [5], [6] in the context of random finite set (RFS) theory [7]. Such MM-PHD-SLAM was applied to mmWave radio SLAM in [4], treating transient targets as clutter in [4], under the assumption they are only visible for short intervals.

In vehicular mmWave networks, the problem of moving objects is particularly relevant: a vehicle mmWave receiver can detect scattered signals by neighboring vehicles with the dynamics for long periods of time [8], called as vehicle scatterer (VS) in this work. Therefore, these VSs cannot be modeled as clutter anymore, leading to incorrect mapping results, even under global map fusion at the base station (BS). For example, in Fig. 1 a VS is detected as a virtual anchor (VA) due to the fundamental limitation in VS estimation, since the VS velocity cannot be obtained from the mmWave measurements.

In this paper, we infer both moving VSs and static landmarks in mmWave radio MM-PHD-SLAM. To handle the aforementioned challenge, we develop an extension of mmWave radio MM-PHD-SLAM [4] that accounts for moving targets and can track them under most conditions, except for fundamentally unidentifiable conditions (e.g., when vehicles are driving in parallel). Our main contributions are (i) a local countermeasure in the MM-PHD-SLAM filter at each vehicle, treating the VS as clutter in [4], under the assumption they are only visible for short intervals, called as vehicle scatterer (VS) in this work. Therefore, these VSs cannot be modeled as clutter anymore, leading to incorrect mapping results, even under global map fusion at the base station (BS). For example, in Fig. 1 a VS is detected as a virtual anchor (VA) due to the fundamental limitation in VS estimation, since the VS velocity cannot be obtained from the mmWave measurements.

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II. SYSTEM MODEL

We consider a mmWave propagation channel wherein static landmarks (a single BS, several VAs, and several scatter points (SPs), indexed by $i$) and moving vehicles are present. Moving vehicles can be mmWave receivers (indexed by $n$) or VSs modeled as clutter anymore, leading to incorrect mapping results, even under global map fusion at the base station (BS). For example, in Fig. 1 a VS is detected as a virtual anchor (VA) due to the fundamental limitation in VS estimation, since the VS velocity cannot be obtained from the mmWave measurements.

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(indexed by $i$). Note that a vehicle $n$ will be a VS indexed by $i$ for another mmWave receiver. The BS periodically transmits a mmWave signal, reflected by specular surfaces (specifying VAs), scattered by SPs and VSs before reaching the receiver on each mmWave-equipped equipment.

1) State Definitions: We denote the vehicle state by $s^n_k = [(x^n_k)^T, \alpha^n_k, \xi^n_k, B^n_k]^T \in \mathbb{R}^7$, where $x^n_k = [x^n_k, y^n_k, z^n_k]^T$, $\alpha^n_k$, $\xi^n_k$, and $B^n_k$ are respectively the location, heading, translation speed, turn-rate, and clock bias. The targets (static landmarks and moving VSs) are modeled as an RFS $\mathcal{X}_k = \{(t^n_k, m^n_k), ..., (t^n_l, m^n_l)\}$ with set density $f(x_k)$. The target index is denoted by $i$, and the state of target $i$ is denoted by $t^n_i = [(x^n_i)^T, (v^n_i)^T, \xi^n_i]^T \in \mathbb{R}^7$, where $v^n_i \in \mathbb{R}^3$ is the velocity. The type of target $i$ is denoted by $m^n_i \in \mathcal{M} = \{\text{BS, VA, SP}\}$. The set cardinality is known for $m \in \{\text{BS, VA, SP}\}$, $v^n_i = 0^T$ and $\xi^n_i = 0$.

2) Dynamical Models: With the known transition density $f_v(s^n_k|s^{n-1}_k)$, the vehicle dynamics are modeled as

$$s^n_k = m_v(s^{n-1}_k) + q^n_k,$$

where $m_v(\cdot)$ is the known transition function, and $q^n_k \sim \mathcal{N}(0, Q)$, with known covariance matrix $Q$. For VS $i$, with known target density $f_v(s^n_i|s^{n-1}_i)$, the single-target dynamics are modeled as

$$t^n_i = m_v(t^{n-1}_i) + q^n_i,$$

where $m_v(\cdot)$ denotes the known transition function and $q^n_i \sim \mathcal{N}(0, Q)$ with known covariance $Q$. Note that for SPs and VAs, $f_v(t^n_i|t^{n-1}_i)$ and $f_v(s^n_i|s^{n-1}_i)$ may differ, as the former represents the assumed model of VAs, which may be simplified compared to the real dynamics $f_v(s^n_i|s^{n-1}_i)$.

3) Measurement Models: Each receiver at vehicles can detect signals coming from targets $(t^n_i, m^n_i) \in \mathcal{X}$. Signal detection depends on a certain detection probability, denoted by $p_{d,k}(s^n_k, t^n_i, m^n_i) \in [0, 1]$, within the field-of-view (FOV) $\mathcal{F}$. Using the channel estimation routine $\mathcal{F}$, vehicle $n$ obtains an unordered measurement set $Z^n_k = \{z^n_{k,1}, ..., z^n_{k,J}\}$, and $J = |Z^n_k|$. Either false alarms (e.g., channel estimation error) or short time invisible transient targets (e.g., people) are regarded as clutter. Clutter is modeled as random, where the number of clutter measurements follows the Poisson distribution. Note that there is no identifier which measurement originates from which target or clutter. The measurement index is denoted by $j$. Following $\mathcal{F}$, non-clutter measurements $z^n_k$ are modeled as

$$z^n_{k,j} = h(s^n_k, x^n_k, m^n_i) + r^n_{k,j},$$

where $h(s^n_k, x^n_k, m^n_i) \sim \mathcal{N}(0, R)$ denotes the measurement noise. Here, $\{r^n_{k,j}\}, \{\theta^n_{k,j}\}, \{\phi^n_{k,j}\}$, and $R$ respectively denote a time-of-arrival (TOA), angle-of-arrival (AOA) in azimuth and elevation, angle-of-departure (AOD) in azimuth and elevation, and the known measurement covariance matrix. Channel parameters for BS, VAs, and SPs follow the geometric relations in $\mathcal{F}$ Appendix B), and VAs are also scatterer and thus the relation of VS is the same as that of SP. Note that from $\mathcal{F}$, the velocity and turn-rate cannot be determined.

III. RECAP OF COOPERATIVE MM-PHD-SLAM FILTER

The MM-PHD-SLAM filter from $\mathcal{F}$ consisting of local filter and global map fusion is briefly described, with $\mathcal{M} = \{\text{BS, VA, SP}\}$. Additional details can be found in $\mathcal{F}$ Section IV, V.

A. Local PHD-SLAM

For a single vehicle, PHD-SLAM is implemented by the Rao-blackwellized particle filter (RBPF), and the vehicle index $n$ is dropped. We represent the vehicle posterior $f_{k|k}(s^n_k) = \sum_{p=1}^{P} p^n_k w^n_k$, where $p^n_k$ is the particle, and $\sum_{p=1}^{P} w^n_p = 1$ is the weight. The corrected PHD conditioned on particle sample is represented as the form of Gaussian mixture (GM), i.e.,

$$D_{k|k}(x^n_k, m^n_i | s^n_{0:k}) = \sum_{q=1}^{Q_k} f_{k|k}^{q} N(x^n_k, \{x^n_k\}_k^{q}(m^n_i), \{P^n_{k|k}^{q}\}_k^{q}(m^n_i)),$$

where $Q_k$ is the number of Gaussians, and $f_{k|k}^{q}, \{x^n_k\}_k^{q}(m^n_i), \{P^n_{k|k}^{q}\}_k^{q}(m^n_i)$ are respectively the Gaussian weight, mean, and covariance.

1) Prediction: The vehicle particle evolves $s^n_k = f_v(s^n_k|s^{n-1}_k)$, and $w^n_{k-1} = w^n_{k-1}$. The predicted map PHD is

$$D_{k|k-1}(x^n_k, m^n_i | s^n_{0:k}) = D_{k|k-1}(x^n_k, m^n_i | s^n_{0:k}) + D_{B,k}(x^n_k, m^n_i | s^n_{0:k}),$$

where $D_{B,k}(x^n_k, m^n_i | s^n_{0:k})$ is the birth PHD, implemented by $\mathcal{F}$ Appendix D-A.

2) Correction: We correct the map PHD for $m$ as

$$D_{k|k}(x^n_k, m^n_i | s^n_{0:k}) = (1 - p_{p^0}(s^n_k, x^n_k, m^n_i)) D_{k|k-1}(x^n_k, m^n_i | s^n_{0:k}) + \nu(z^n_k, x^n_k, m^n_i | s^n_{0:k}),$$

where $c(z^n_k)$ is the clutter intensity and $\nu(z^n_k, x^n_k, m^n_i | s^n_{0:k}) = p_{p^0}(s^n_k, x^n_k, m^n_i) D_{k|k-1}(x^n_k, m^n_i | s^n_{0:k}) g(z^n_k, x^n_k, s^n_{0:k})$. The corrected vehicle weight is $w^n_k \propto w^n_{k-1} w^n_{k-1}$, with $\mathcal{F}$ Appendix C.

$$\nu(z^n_k, x^n_k, m^n_i | s^n_{0:k}) = \int \nu(z^n_k, x^n_k, m^n_i | s^n_{0:k}) d|x^n_k|.$$
proximity matrix C based on the Mahalanobis distance; (ii) determining matched components \((q_1, q_2)\) between \(D_1\) and \(D_2\) based on the proximity matrix \(C\); (iii) assigning weights \(\beta_1^{q_1} = \beta_2^{q_2} = 1/2\) to each matched pair, and assigning weights \(\beta_1^{q_3}, \beta_2^{q_3} \in \{1/2, 1\}\) to unmatched components \([1]\). Note that missed detections are more critical than false alarms in the SLAM applications. To handle missed detections in the VS map, we adopt the AA approach, taking the union of the involved densities, resulting in map fusion with the minimum information loss \([1]\).

2) Downlink PHD Map Update at Vehicle: Vehicle \(n\) overwrites the fused map PHD as \(D_{k|k}(x_k, m|s^n_{0:k}) = D^n_{k|k}(x_k, m), \forall p\).

C. Impact of VS

In the presence of VS, the following effects will be observed. VS on parallel trajectories to the ego vehicle lead to additional entries in the VA PHD, as they appear similar to large reflecting surfaces parallel to the ego vehicle, with slowly moving VA locations. Then, SLAM accuracy is adversely affected.

IV. COUNTERMEASURES TO TRACK VEHICLE SCATTERERS

We describe the proposed countermeasure process, added on local PHD-SLAM (Sec. III-A) and on global map fusion (Sec. III-B) as shown in Fig. 2. We drop the target type \(m\) except the process of vehicle particle correction.

A. Countermeasures in Local PHD-SLAM

To ensure a unified state definition for all targets, we replace \(x_k\) with the target state \(t_k\) for the Bayesian recursion with the transition density and the measurement, and denote the corrected map PHD, conditioned on vehicle particle \(s^n_{0:k}\), by \(D_{k|k}(t_k|s^n_{0:k})\), represented as the GM form.

1) Prediction: To exploit target dynamics, we include the target transition density \(f_{VS}(t_k|t_{k-1})\) in PHD map prediction:

\[
D_{k|k-1}(t_k|s^n_{0:k}) = D_{k|k-1}(t_k|s^n_{0:k}) + P_S \int f_{VS}(t_k|t_{k-1}) D_{k-1|k-1}(t_{k-1}|s^n_{0:k-1})dt_{k-1},
\]

where \(D_{k|k-1}(t_k|s^n_{0:k})\) is the birth PHD. In the birth PHD, we set \(t^n_{k|p,q} = (x^n_{k|p,q}, \nu^n_{k|p,q})^\top\), \(v^n_{k|p,q} = \sum_{n=1}^N \nu^n_{k|p,q} w^n_{k|p,q}\), and \(T^n_{k|p,q} = \text{blkdiag}(T^n_{k|p,q}, V^n_{k|p,q})\), where for VS, we can compute \(x^n_{k|p,q}\) and \(P^n_{k|p,q}\), similarly to SP birth PHD \([4]\), using the cubature Kalman filter (CKF). Due to the nonlinear measurement model, and fact that the VS velocity and turn-rate in the VS birth PHD cannot be observed, correction leads to overly concentrated covariance estimates \([12]\). To address this, we adopt the dithering methods, mitigating approximation error for target estimates in the CKF \([3]\).

2) Correction: The predicted map PHDs for all \(m\) are utilized in correction, and thus the likelihood function for VS map PHD information \(\nu(z, t_k, VS|s^n_{0:k})dt_k\) is additionally considered. With the introduction of \(\psi^p(z) = c(z) + \sum_{s \in \mathcal{Z}} \nu(z, t_k, VS|s^n_{0:k}) dt_k\), the likelihood function is computed as \(p^p_{k|k} = \sum_{z \in \mathcal{Z}_k} \psi^p(z)\). The VS map PHD is corrected as follows:

\[
D_{k|k}(t_k, VS|s^n_{0:k}) = (1 - \rho_D(s^n_{0:k}, VS))D_{k|k-1}(t_k, VS|s^n_{0:k}) + \sum_{z \in \mathcal{Z}_k} \frac{\nu(z, t_k, VS|s^n_{0:k})}{\psi^p(z)}.
\]

B. Countermeasures in Global Map Fusion

For map fusion at the BS, we first change the computation of the average map \([7]\) by placing the accurate ego state in the averaged VS map PHD since the ego state is available with high accuracy. Second, we compute the fusion weights to strike an appropriate balance between missed detections and false alarms, instead of assigning the fusion weights evenly \([4]\).

1) Placing the Ego Vehicle in the Average Map: Compared to \([7]\), the averaged map VS PHD at vehicle \(n\) exploits the self-vehicle posterior density \(f_{k|k}(s^n_{0:k})\). Then,

\[
\bar{D}^n_{0:k}(t_k) = F'_{AA}(\bar{D}^n_{0:k}(t_k), f_{k|k}(s^n_{0:k})),
\]

where \(\bar{D}^n_{0:k}(t_k) = \sum_{p=1}^P D_{k|k}(t_k|s^n_{0:k}, VS) u^n_{k|p}\) is the average VS PHD, similarly to \([7]\). Here, \(F'_{AA}(\cdot)\) is a newly developed AA fusion operator for this global countermeasure, different from \(F_{AA}(\cdot)\) in Sec. III-B. A huge number of Gaussians are reduced by the pruning and merging (PM) step \([14]\ Table IV), and then \(\bar{D}^n_{0:k}(t_k) \approx \sum_{q=1}^Q q^T N(t_k; T^n_{0:k}, \Sigma^n_{0:k})\).

We assume that the self-vehicle posterior density \(f_{k|k}(s^n_{0:k})\) follows the Gaussian distribution, and thus being seen as the PHD with one Gaussian with the unity weight \(f_{k|k}(s^n_{0:k}) = N(t_k; t^n_{k|k}, T^n_{k|k})\). To determine the fusion weights, we generate a binary proximity vector \(c \in \{0, 1\}^Q\), with element \(c_q = 1\) if and only if

\[
\text{d}_{\text{MSM}}(N(x_k; x^n_{k|k}, \Sigma^n_{k|k}), N(x_k; x^n_{k|k}, \Sigma^n_{k|k})) < T_{\text{MD}},
\]

depending on the accumulated FOV \([4]\) if component is determined as false alarm, \(\beta = 1/2\), otherwise, \(\beta = 1\).
Consequently, the fused map PHD at the BS is modified as
\[
\Delta q \text{ is matched to Gaussian}
\]
At the BS, there is no measurement, and
\[
\text{Matched Targets} \quad \text{Unmatched Targets}
\]
\[
D_{MSM} \mid k
\]
\[
C \alpha \text{ ance, the Gaussian uncertainty is determined by}
\]
\[
\text{of missed detection, we set}
\]
\[
\beta_1^q = \begin{cases} 
0, & c_q = 1, \\
1, & \text{otherwise},
\end{cases}
\]
and \(\beta_2 = 1\). Here, \(c_q = 1\) indicates that self-vehicle Gaussian is matched to Gaussian \(q\) in VS PHD. This ensures that matched GM components in the VS PHD are removed and replaced with a weighted vehicle posterior.

2) Map Fusion: At the BS, there is no measurement, and thus the fused map PHD is predicted without the birth process
\[
\bar{D}_{k}^{BS}(t_k) = \mathbb{P}_S \int f(t_k|t_{k-1}) \bar{D}_{k-1}^{BS}(t_{k-1}) dt_{k-1}.
\]
Consequently, the fused map PHD at the BS is modified as
\[
\bar{D}_{k}^{BS}(t_k) = F_{AA}^{BS}(\bar{D}_{k-1}^{BS}(t_k), \bar{D}_{k}^{U}(t_k)).
\]
The PHDs in (10) are also represented as the GM form:
\[
\bar{D}_{k}^{BS}(t_k) = \sum_{q_1=1}^{Q_{BS}} \beta_1^{q_1} \eta^{q_1} N(t; \mathbf{t}^{q_1}, \mathbf{T}^{q_1}) + \sum_{q_2=1}^{Q_{BS}} \beta_2^{q_2} \eta^{q_2} N(t; \mathbf{t}^{q_2}, \mathbf{T}^{q_2}).
\]
To determine the fusion weights \(\beta_1^{q_1}\) and \(\beta_2^{q_2}\), we generate a matrix \(\mathbf{C} \in \{0, 1\}^{Q_{BS} \times Q_{BS}}\), indicating the proximity of distance between two Gaussians, with \(C_{q_1,q_2} = 1\) if and only if the following two conditions are satisfied:
\[
d_{MSM}(\mathcal{N}(\mathbf{x}; \mathbf{x}^{q_1}, \mathbf{P}^{q_1}), \mathcal{N}(\mathbf{x}; \mathbf{x}^{q_2}, \mathbf{P}^{q_2})) < T_{MD}^{BS},
\]
\[
d_{MSM}(\mathcal{N}(\mathbf{v}; \mathbf{v}^{q_1}, \mathbf{V}^{q_1}), \mathcal{N}(\mathbf{v}; \mathbf{v}^{q_2}, \mathbf{V}^{q_2})) < T_{MD}^{BS},
\]
where \(T_{MD}^{BS}\) is a threshold. The fusion weights are finally assigned as follows:

- **Matched Targets** (i.e., \(C_{q_1,q_2} = 1\)): The condition notes that both two targets with states \(t^{q_1}\) and \(t^{q_2}\) are matched, and then two VS densities need to be merged. To weigh the matched densities according to their covariance, the Gaussian uncertainty is determined by \(\rho = \text{trace} \left( \mathbf{T} \right) / \dim(\mathbf{T})\) [13]. Then, we compute the weights as
\[
\beta_1^{q_1} = \frac{1}{\rho^{q_1}}, \quad \beta_2^{q_2} = \frac{1}{\rho^{q_2} + 1 / \rho^{q_2}}.
\]
- **Unmatched Targets** (i.e., \(C_{q_1,q_2} = 0\)): The condition notes that the targets \(t^{q_1}\) and \(t^{q_2}\) are unmatched. If \(\sum_q C_{q_1,q_2} = 0\), then the Gaussian \(q_2\) is not be associated with any Gaussian \(q_1\), indicating that Gaussian \(q_2\) could be a newly detected target or false alarm. To avoid the risk of missed detection, we set \(\beta_2^{q_2} = 1\). If \(\sum_q C_{q_1,q_2} = 0\), then Gaussian \(q_1\) is not associated with any Gaussian \(q_2\), indicating that Gaussian \(q_1\) could be the previously detected target or previous false alarm, possibly. Here, we can make a decision based on the accumulated VOV.

4. The MSM metric can also be used in a Hungarian algorithm.

5. Process noise \(q_{ik}\); time interval \(\Delta\), measurement noise covariance \(\mathbf{R}\); BS location \(x_{BS}\), VA locations \(x_{VA,1}, x_{VA,2}, x_{VA,3}, x_{VA,4}\); threshold for PM steps (for the reduction of Gaussian components and the weighted sum of Gaussians); threshold for target detection \(T_{VA}, T_{VS} = T_{SP}\); birth weight; Poisson mean for clutter measurement; landmark visibility and FOV range \(r_{SP} = r_{VS} = 50\) m.

### V. SIMULATION RESULTS AND DISCUSSIONS

#### A. Simulation Setup

To demonstrate the developed PHD-SLAM filter with proposed countermeasures to handle VSs, we consider a scenario that VS measurements are added into mmWave radio propagation environment [4]. We consider two vehicles which move parallel on the circular road. The same values in [4 Sec. VI-A] are adopted for the parameters.

For dynamics of vehicle states (1) and VSs (2), we respectively adopt (4) eq. (25)) in polar coordinates and (10) Sec. V-B] in Cartesian coordinates, rendering the VS state identifiable over time. We set \(q_k = [1, 1, 0.1, 3, 3, 0.1, 0.05]^{\top}\), with units m, m, m/s, m/s, m/s, rad/s. For generating \(v^i\) and \(\xi^i\) in \(D_{n,k}(t_k|\mathbf{r}_{0,k})\) of (7), we set \(\mathbf{v} = \text{diag}([100, 100, 0.09])\) and \(\sigma_v = \pi / 2\), and \(v^i \sim N(0, \mathbf{V})\) and \(\xi^i \sim U([-0.2\pi, 0.2\pi])\). In VS prediction, \(\mathbf{T}_d = \text{diag}([0.3, 0.3, 0.01, 0.01, 0.03, 0.03])\). The longitudinal velocity \(\xi_v\), rotational velocity \(\xi_r\) are assumed to be known since the knowledge of inertial sensor of board is available. Four SPs are located at \([-55, 55, 0, 0, 1.5, 0, 0, 0, 0.3]\), and \(s_0 = [60, 73.0, 0, 0, 2, 22.22, \pi / 10, 300]^{\top}\), with units m, m, m, rad, m/s, rad/s, and m. The initial prior of the vehicle state is sampled from \(\mathcal{N}(s_0, s_0^0, s_0^0)\), where \(s_0 = \text{diag}([0.3^2, 0.3^2, 0.01^2, 0, 0, 0.3^2])\). The longitudinal velocity \(\xi_v\), rotational velocity \(\xi_r\) are assumed to be known since the knowledge of inertial sensor of board is available. Four SPs are located at \([-55, 55, 0, 0, 1.5, 0, 0, 0, 0.3]\), and \(s_0 = [60, 73.0, 0, 0, 2, 22.22, \pi / 10, 300]^{\top}\), with units m, m, m, rad, m/s, rad/s, and m. The initial prior of the vehicle state is sampled from \(\mathcal{N}(s_0, s_0^0, s_0^0)\), where \(s_0 = \text{diag}([0.3^2, 0.3^2, 0.01^2, 0, 0, 0.3^2])\).
bias and heading). For the filter from [4] and the proposed MM-PHD-SLAM filter, we observe similar trends as in mapping, due to the fact that vehicle and map are correlated at every time step. The RMSEs are similar at first. However, after starting map fusion at time 5, and after a few time steps, the fused map is becoming informative, then the RMSEs diverge.

VI. CONCLUSIONS

We have proposed countermeasures to handle moving VSs, in cooperative mmWave radio PHD-SLAM. We demonstrate that without these countermeasures, standard PHD-SLAM fails, due to false targets raised by the VS. We confirmed that the proposed filter can track both moving VSs and static landmarks, while simultaneously localize the vehicles.

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