Multi-Object Tracking using Poisson Multi-Bernoulli Mixture Filtering for Autonomous Vehicles

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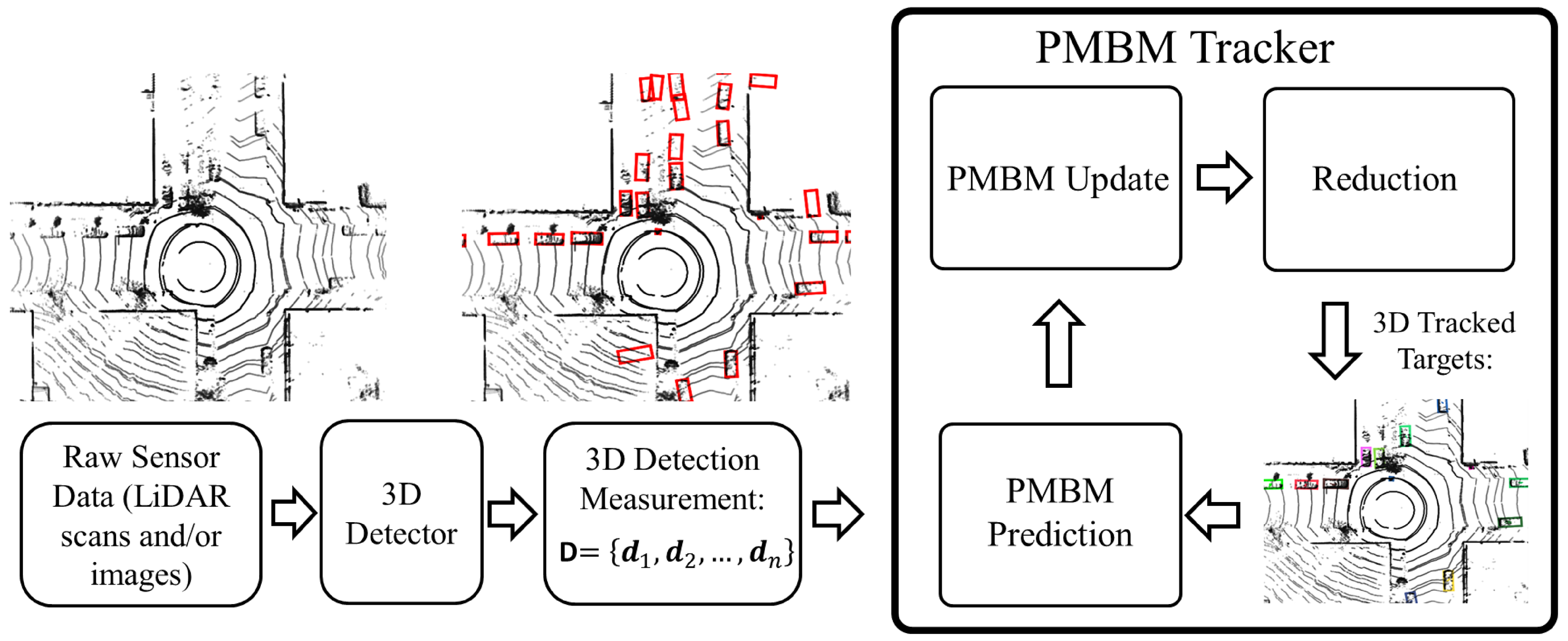
◆ Highlights:

- We Propose a PMBM filter to solve the amodal MOT problem for autonomous driving applications. To the best of our knowledge, this represents a first attempt for employing an RFS-based approach in conjunction with 3D LiDAR data and neural network-based detectors.
- Our PMBM tracker has low-complexity, and it can run at an average of 20Hz on a standard desktop PC.
- We validate and test the performance of our PMBM tracker using two extensive open datasets provided by two industry leaders – Waymo and Argoverse.

◆ Multi-Object Tracking (MOT) Main Challenges:

(1) Uncertainty in the number of objects. (2) Uncertainty regarding when and where the objects may appear and disappear. (3) Uncertainty in objects' states.

- ❑ **Detected Objects:** Tracked objects that have been detected at least once. Multi-Bernoulli Mixture (MBM) RFS is used to represent detected objects.
- ❑ **Undetected Objects:** Potential objects that have not been detected. Poisson RFS, also named Poisson Point Process (PPP) is used to model undetected objects.



Our PMBM Tracker System Architecture

◆ Object State:

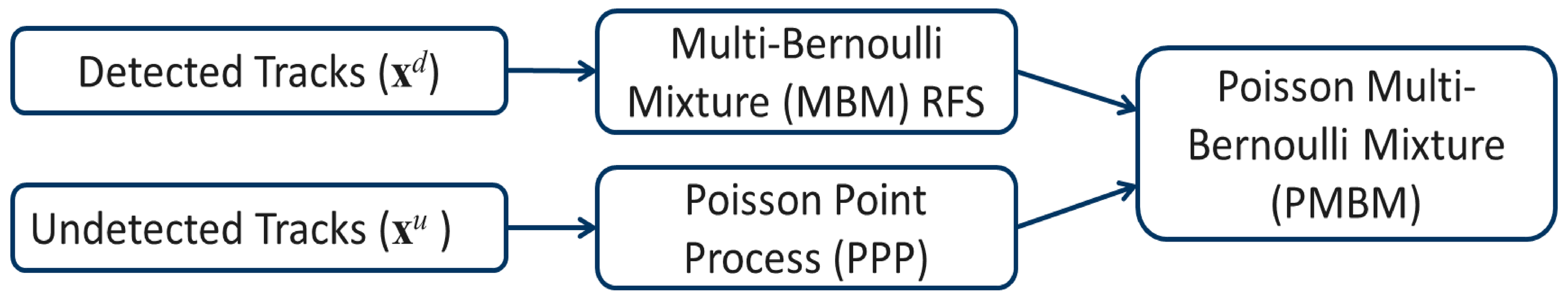
Under this work, our PMBM tracker is designed as a point-based tracker. The object state used in this work is defined as $\mathbf{x} = [x, y, v_x, v_y]$. The reason for this are as follows:

- *z* value does not change dramatically for consecutive frames.
- The dimension of the objects are already precise from a neural network-based 3D detector.
- Reducing the state dimension inherently enables the tracking system operate at a lower computational cost for real-time performance.

◆ PMBM Density:

In our RFS-based tracker, Poisson point process (PPP) is used to represent Undetected Objects, multi-Bernoulli mixture (MBM) RFS is used to model Detected Objects.

$$PMBM_t(\mathbf{x}) = \sum_{\mathbf{x}^u \uplus \mathbf{x}^d = \mathbf{x}} PPP_t(\mathbf{x}^u) MBM_t(\mathbf{x}^d)$$



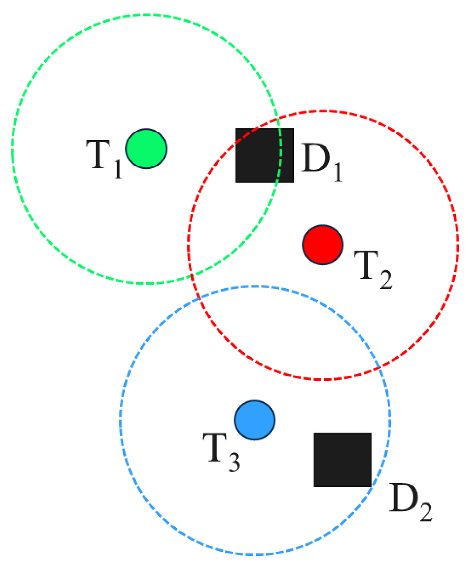
◆ PMBM Prediction:

Conjugacy property of PMBM filter: If the prior is in PMBM form, then the distribution after Bayesian prediction and update steps will also be PMBM form.

$$PMBM_{t+1|t}(\mathbf{x}_{t+1}) = \int p(\mathbf{x}_{t+1} \mid \mathbf{x}_t) PMBM_{t|t}(\mathbf{x}_t) \delta \mathbf{x}_t$$

◆ Data Association Hypotheses

Each measurement, either it is a newly detected target, a previously detected target, or a false positive detection. We form different global association hypotheses from possible combinations of the single target hypothesis (STH).



One measurement can only be associated to one object in one global association hypotheses.

◆ PMBM Update

(1) Update of Detected Objects without associated detections/measurements.
(2) Update of Detected Objects with associated detections/measurements.
(3) Update of Undetected Objects without associated detections/measurements.
(4) Update of Undetected Objects with associated detections/measurements
-> Update of new objects tracked for the first time.

◆ Reduction

- Pruning: Remove objects and global hypotheses with low weights.
- Capping: Set an upper bound for the number of global hypotheses and detected objects.
- Gating: Limit the search distance for data association.
- Recycling: For detected objects with lower probability of existence, instead of discarding these objects, we recycle them by moving them from detected object set to undetected object set.
- Merging: Merge these identical non-unique global hypotheses into one.

◆ Experimental Results

3D MOT evaluation results on Argoverse dataset

Method	Split	Class	MOTA (Primary) (%)	MOTP	#False Positive	#Misses
Argoverse Baseline	test	Vehicle	65.90	0.34	15,693	23,594
Our PMBM tracker	test	Vehicle	**71.67**	0.34	8,278	24,165
Argoverse Baseline	test	Pedestrian	48.31	0.37	4,933	25,780
Our PMBM tracker	test	Pedestrian	**48.56**	0.4	5,924	24,278

3D MOT evaluation results on Waymo dataset

Method	Split	Class	MOTA (Primary) (%)	MOTP	False Positive (%)	Misses (%)
Waymo Baseline	test	All	25.92	0.263	13.98	64.55
Argoverse Baseline	test	All	29.14	0.270	17.14	53.47
Probabilistic KF	test	All	36.57	0.270	8.32	54.02
Our PMBM tracker	test	All	**38.51**	0.270	7.74	52.86

◆ Conclusion

We propose a PMBM tracker to solve the 3D amodal MOT problem with 3D LiDAR data for autonomous driving applications. Our framework can naturally model the uncertainties in MOT problem. The experimental results on Waymo and Argoverse datasets demonstrate that our approach outperforms previous state-of-the-art methods by a large margin.