3D Multi-Object Tracking for Autonomous Driving

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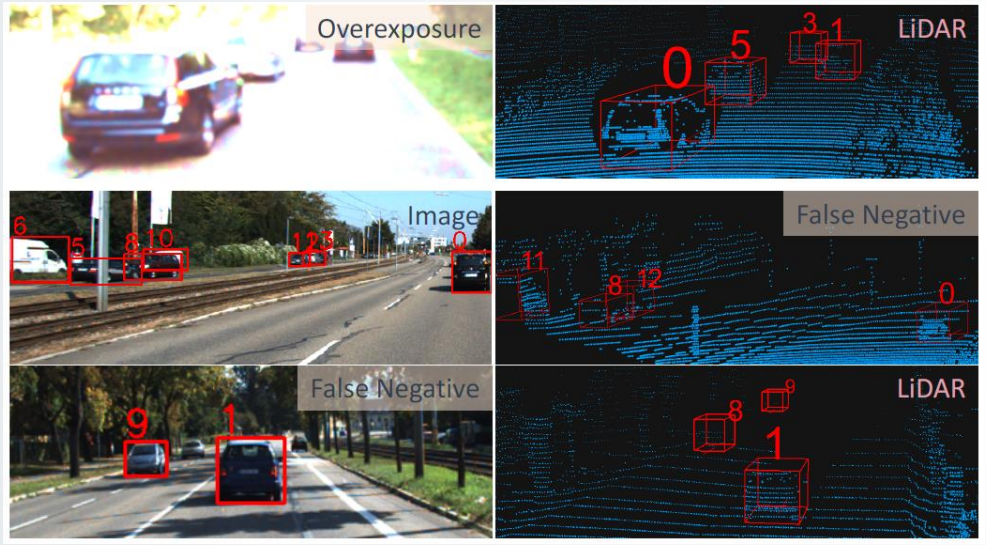
1 Introduction

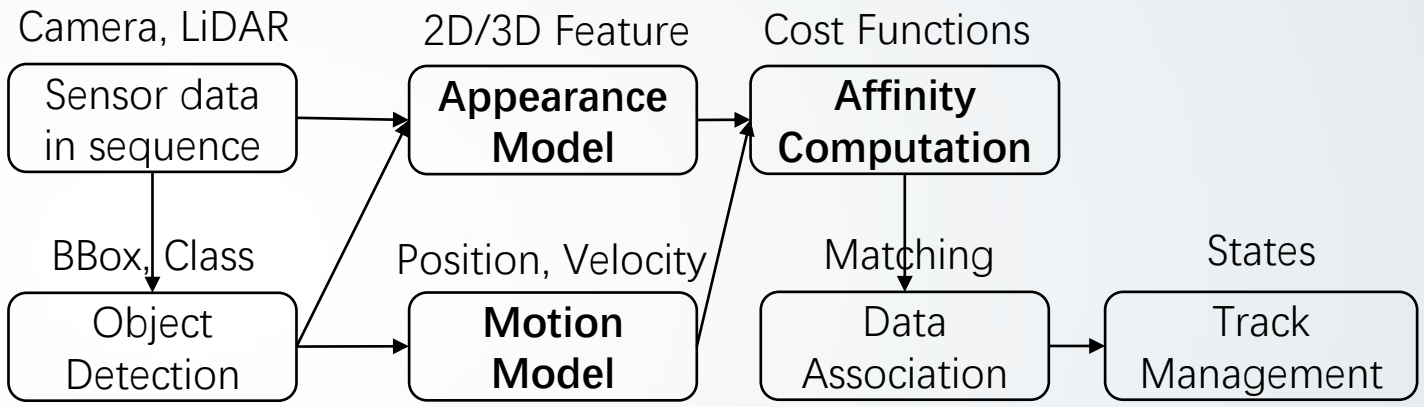
Background for autonomous system and multiple object tracking (MOT)

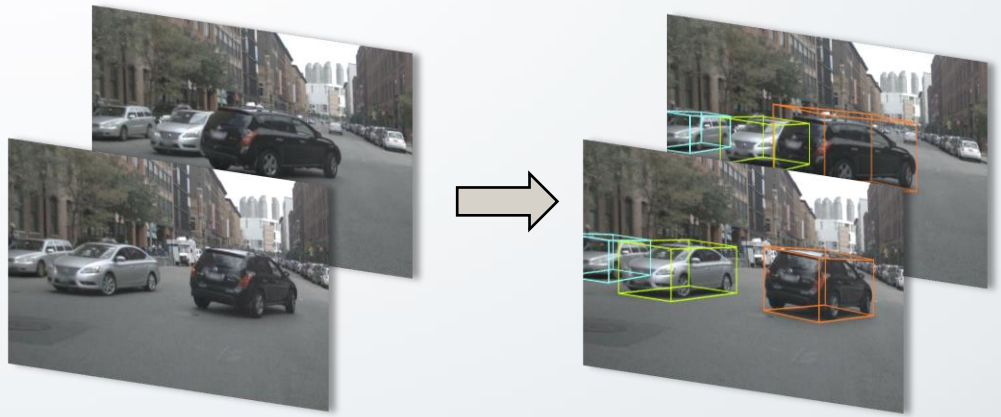
01 Background



Sensor Reliability

Multi-Object Tracking Pipeline





2 Related Work

State-of-the-art MOT approaches

02 Related Work

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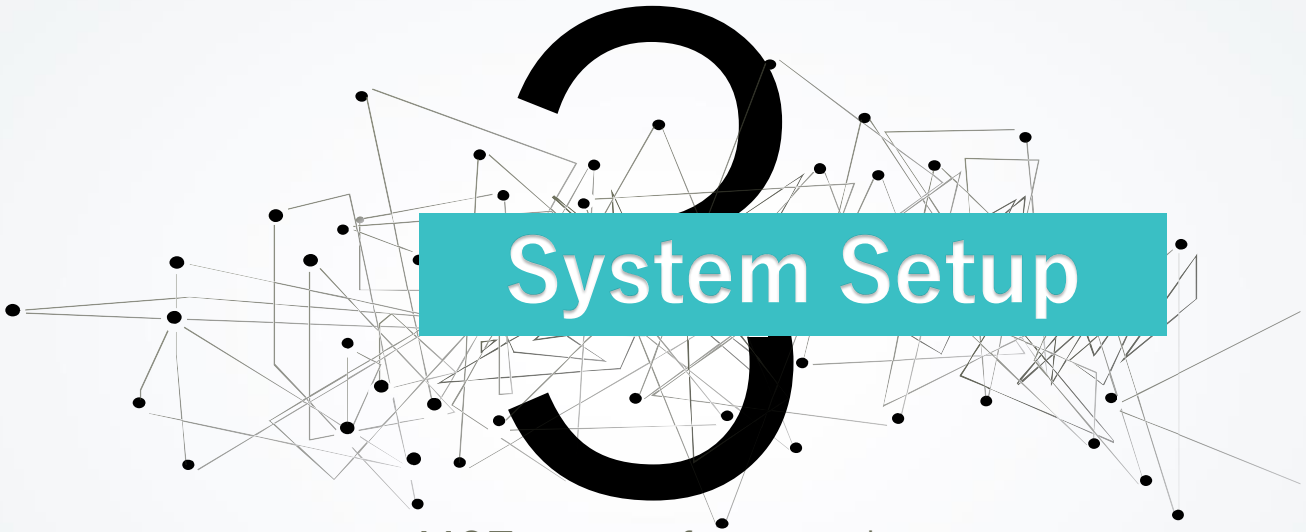
Method		Appearance		Motion		Dissimilarity Computation (Total Cost)
		Feature Extractor	Branch Cost	Motion Model	Branch Cost	
Filter Tracker	PMBM [1]	X	-	Poisson Multi-Bernoulli Mixture	Multi-Bernoulli	-
	Deep-SORT [2]	ResNet	Cosine Distance	Kalman Filter	IoU + Mahalanobis	Motion Cost
DNN Tracker	MASS [3]	SIFT	Masked Correlation	Custom	IoU + Euclidean	Weighted Sum
	End-to-End [4]	Siamese Network (VGG16)	-	Fully Connected (Occupancy Grid)	-	Fully Connected
	Hu et al. [5]	Faster RCNN	Exponential L1 Norm	Two LSTMs	IoU	Weighted Sum
Multi-Modality Tracker	mmMOT [6]	VGG16 + PointNet + Attention Map	Absolute Subtraction	X	-	Appearance Cost
Ours		ResNet + PointNet + Fusion Net	Absolute Subtraction	Kalman Filter	IoU + Mahalanobis	Weighted Sum



3 System Setup

MOT system framework

03 System Setup

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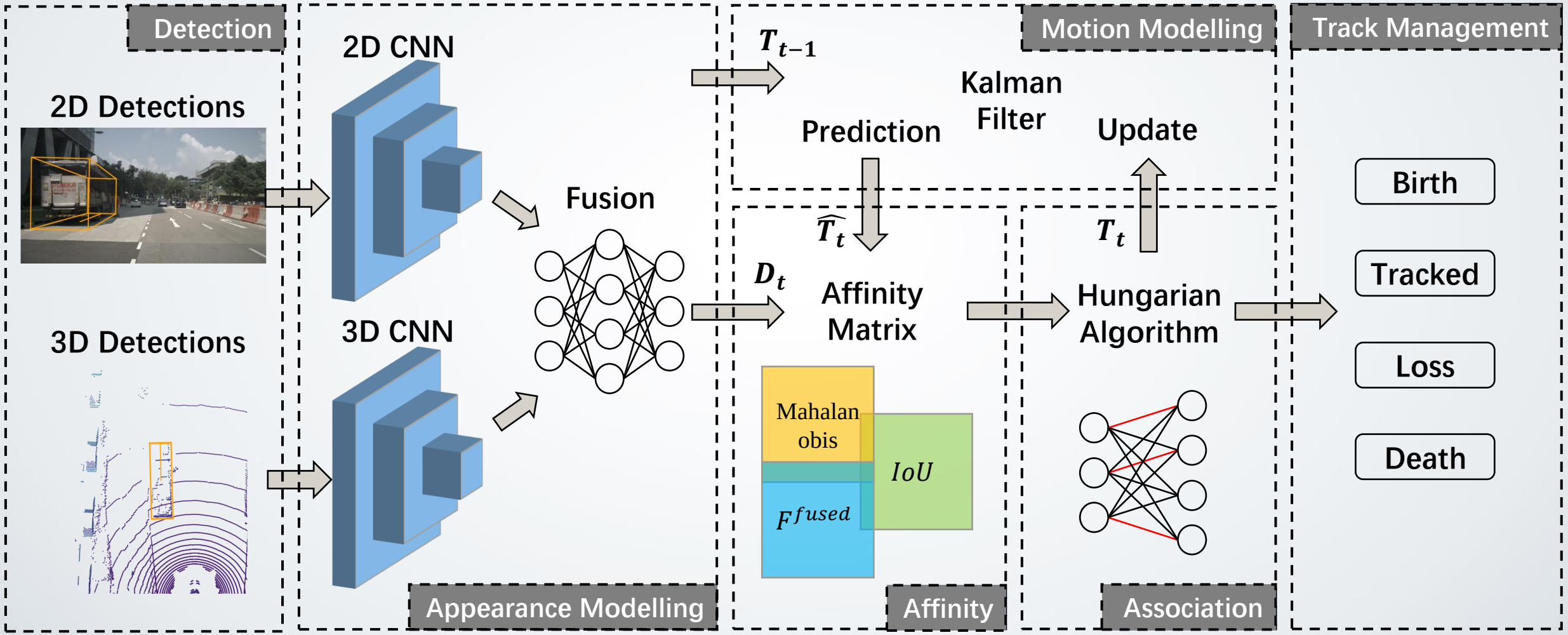

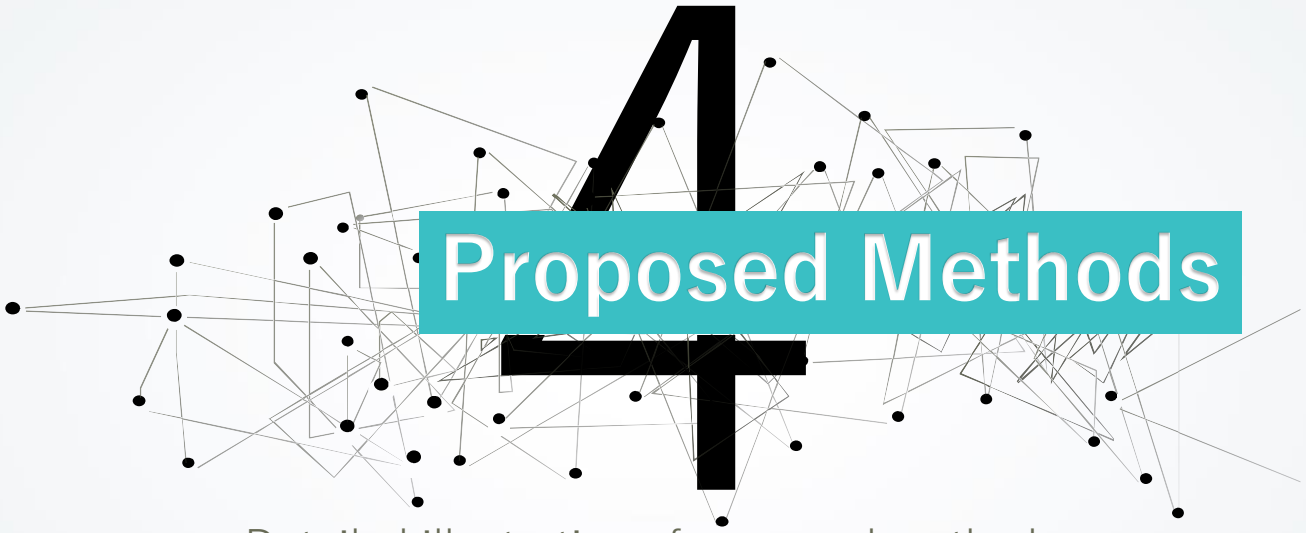

4 Proposed Methods

Detailed illustration of proposed methods

04 Proposed Methods

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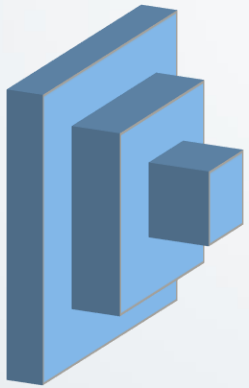
Image Feature Extractor

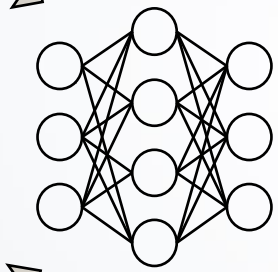
Finetune:
ResNet-50 /
VGG-16

Siamese Networks

Point Cloud Feature Extractor

Finetune:
PointNet (skip pooling)





Feature Fusion

Fully Convolution Layer or Attention map

$$G = sigmoid(conv(F, k))$$

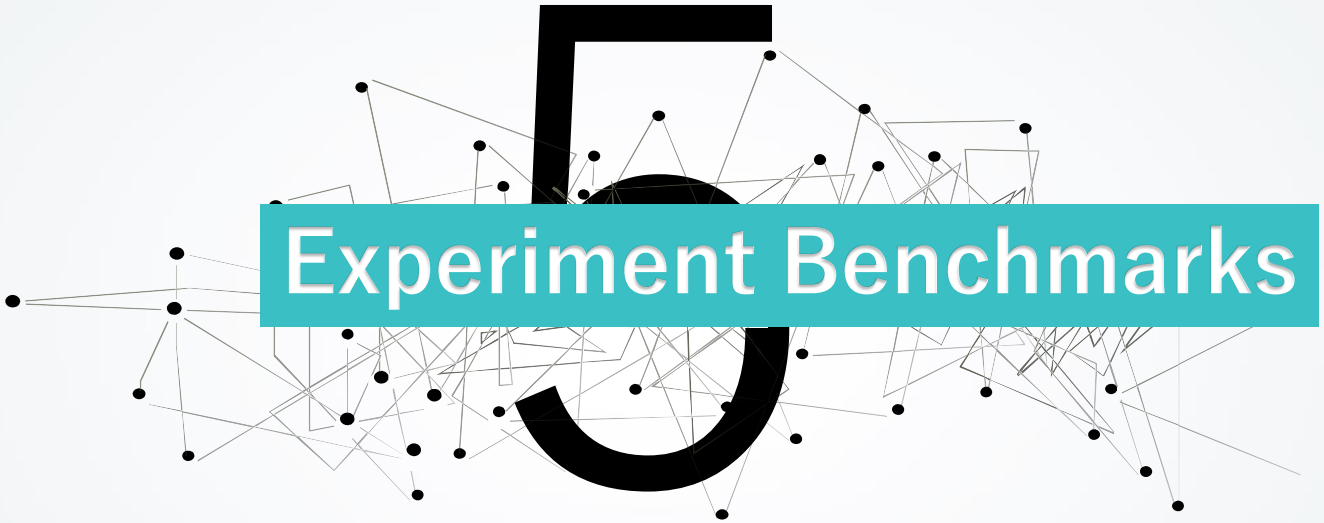
$$F_{fused} = [G1 * conv(F1, k1) + G2 * conv(F2, k2)] / (G1 + G2)$$

Kalman Filter

P: state covariance
Q: process covariance
R: measurement covariance

Affinity Matrix

$$A(i,j) = w_{loc} \cdot A_{loc}(i,j) + w_{app} \cdot A_{app}(i,j) + w_{iou} \cdot A_{iou}(i,j)$$



5 Experiment Benchmarks

05 Experiment Benchmarks

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MOT Benchmarks

- **Kitti**
  - 21 training sequences
  - 29 test sequences
- **NuScenes**
  - 1000 scenes
  - 40k keyframes

Metrics:

- Mostly Tracked (MT)
- Fragments (FM)
- Mostly Lost (ML)
- ID switches (IDSW)
- $MOTA = 1 - \frac{FN+FP+IDSW}{GT} \in (-\infty, 1]$
- $MOTP = \frac{\sum_{t,i} d_{t,i}}{\sum_t c_t} \in [0,1]$

Method	MOTA↑	MOTP↑	Prec.↑	Recall↑	FP↓	FN↓	ID-s↓	Frag↓	MT↑	ML↓	FPS↑
AB3DMOT	69.22	**86.76**	85.78	89.18	1975	1446	**0**	**71**	75.46	3.7	203.4
mmMOT	**79.46**	85.44	93.45	**88.84**	791	**1417**	75	272	**76.85**	**2.32**	13.34
ours(motion)	74.34	85.72	**94.73**	81.93	**572**	2270	10	75	59.26	18.52	**240.2**
ours(motion+appearance)	77.71	85.68	94.12	85.80	676	1791	10	96	63.43	5.56	42.71