Continuous Models for Scene and Traffic Participant Interactions in Road Scene Understanding

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Monocular Road Scene Understanding

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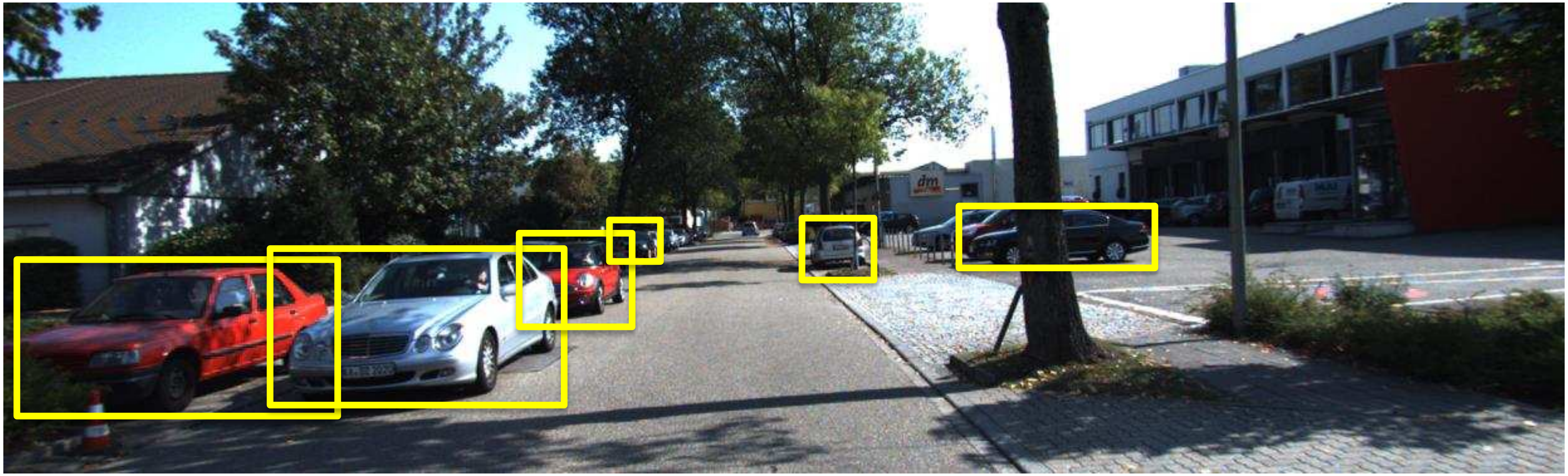

- Object detection: Detect various traffic participants (TP)

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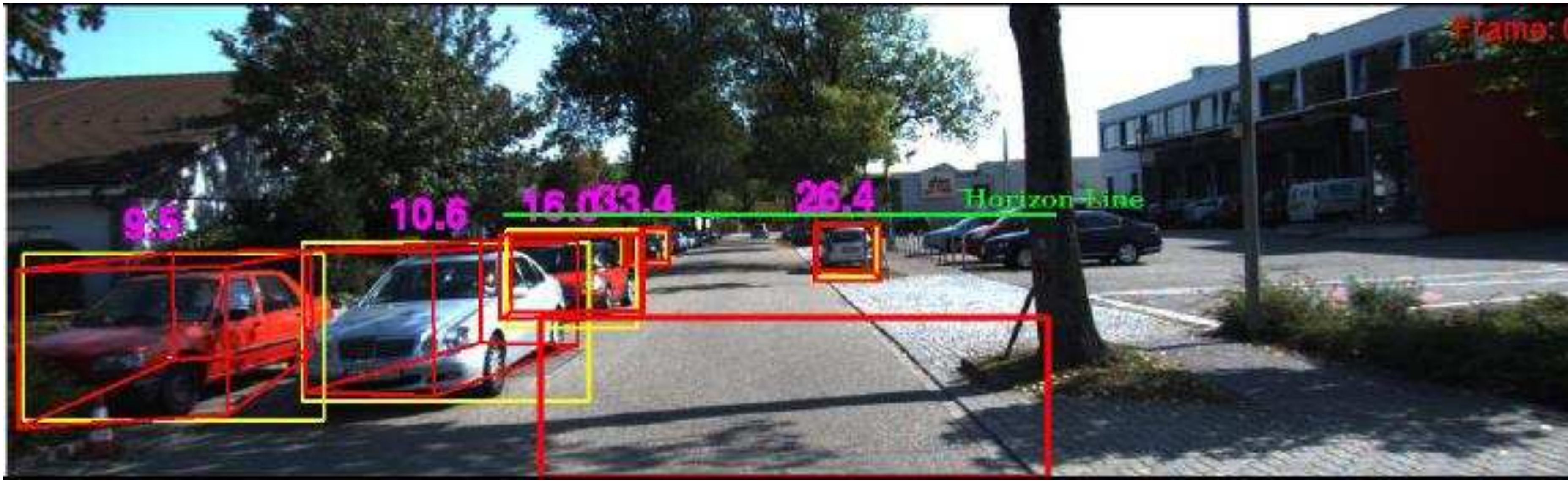

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- Object localization: position and orientation of TPs in 3D

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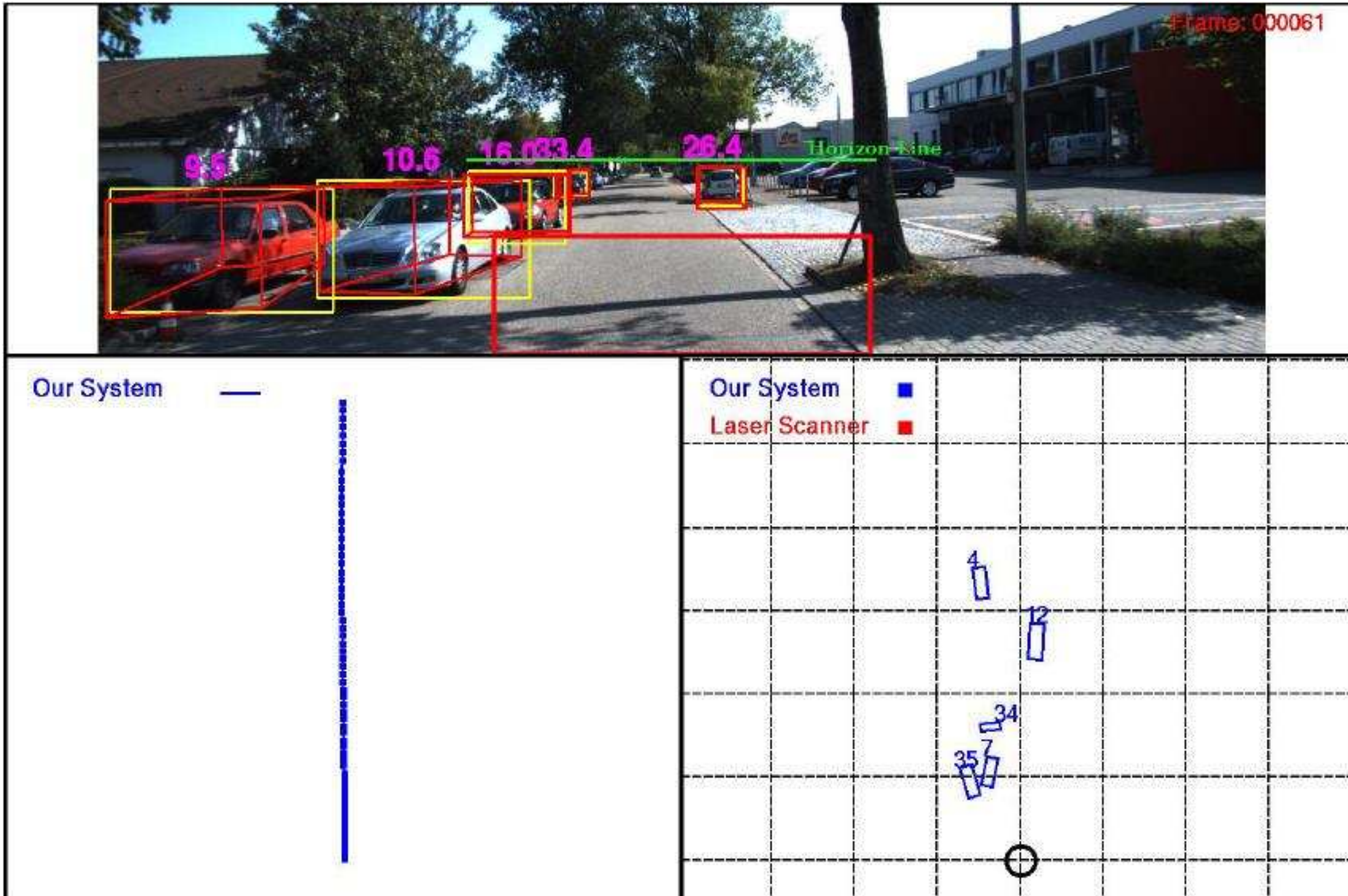
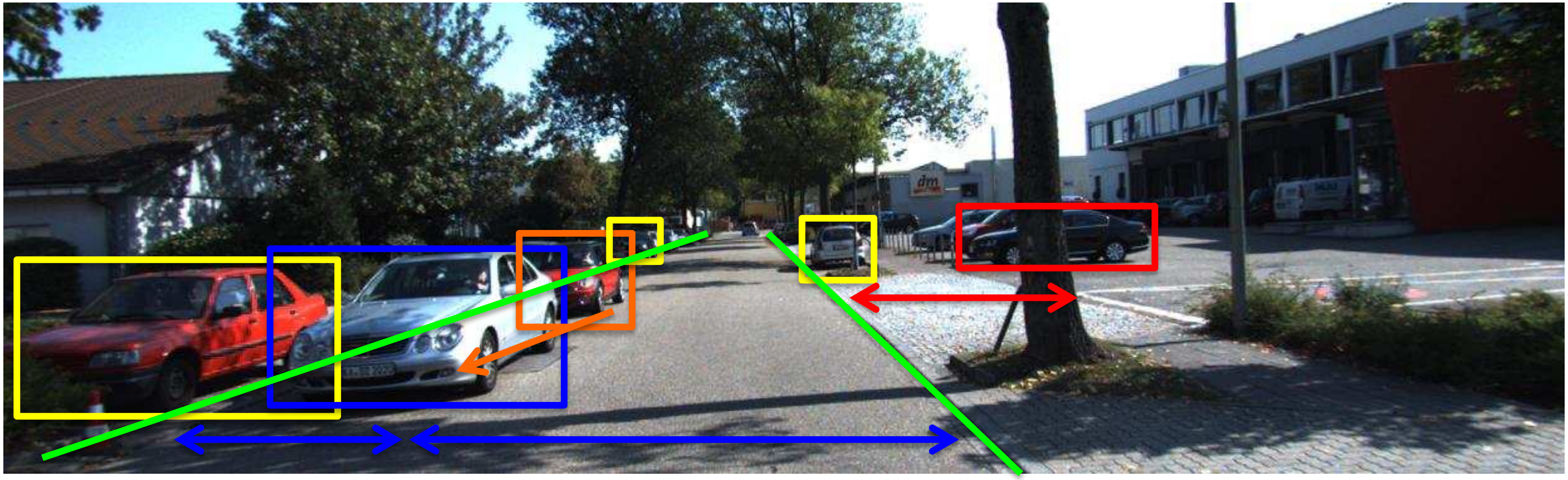


Monocular Road Scene Understanding

- Object detection: Detect various traffic participants (TP)
- Object localization: position and orientation of TPs in 3D
- Detect various scene elements (SE)

Monocular Road Scene Understanding



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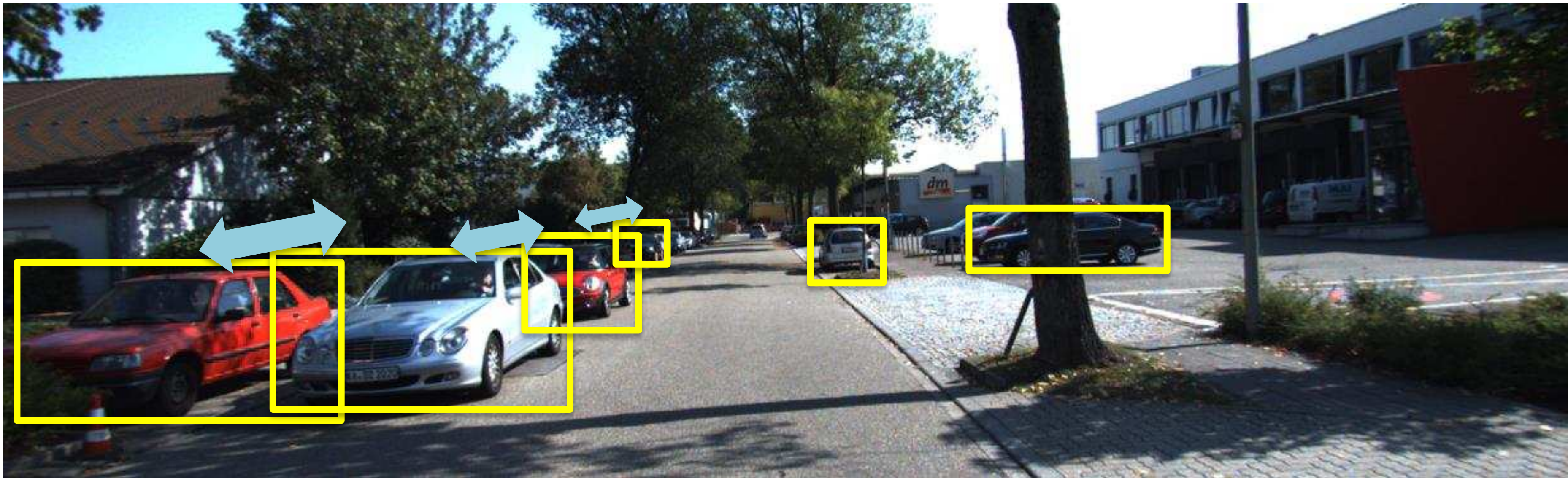
- Object localization: position and orientation of TPs in 3D
- Detect various scene elements (SE)
- Enforce relations between TPs and SEs

Monocular Road Scene Understanding



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- Enforce relations between TPs and SEs
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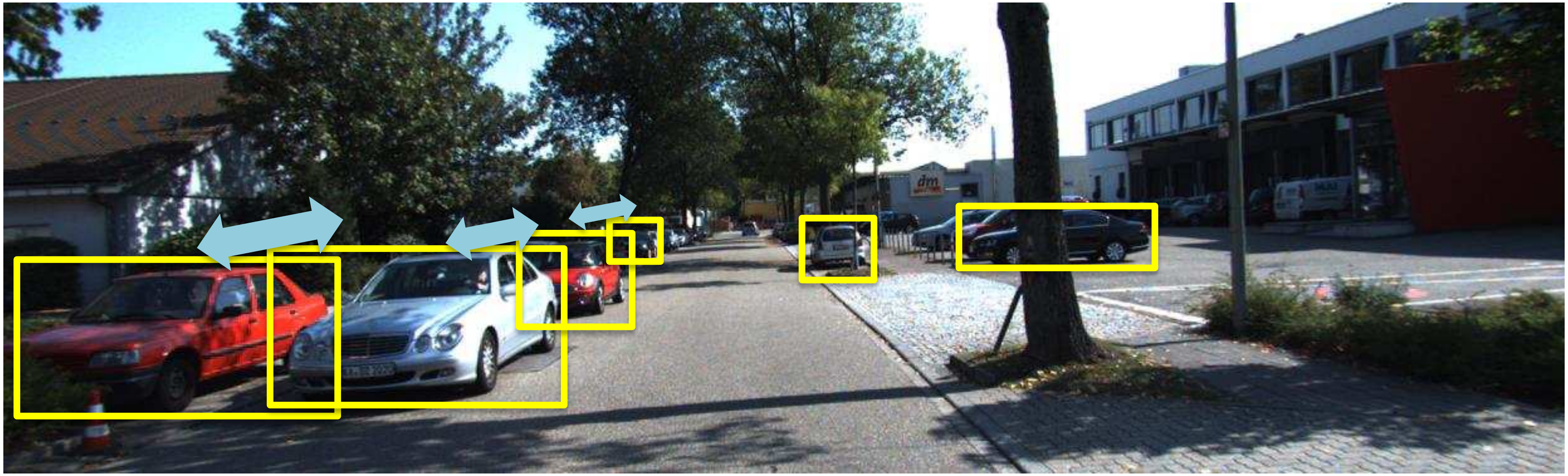
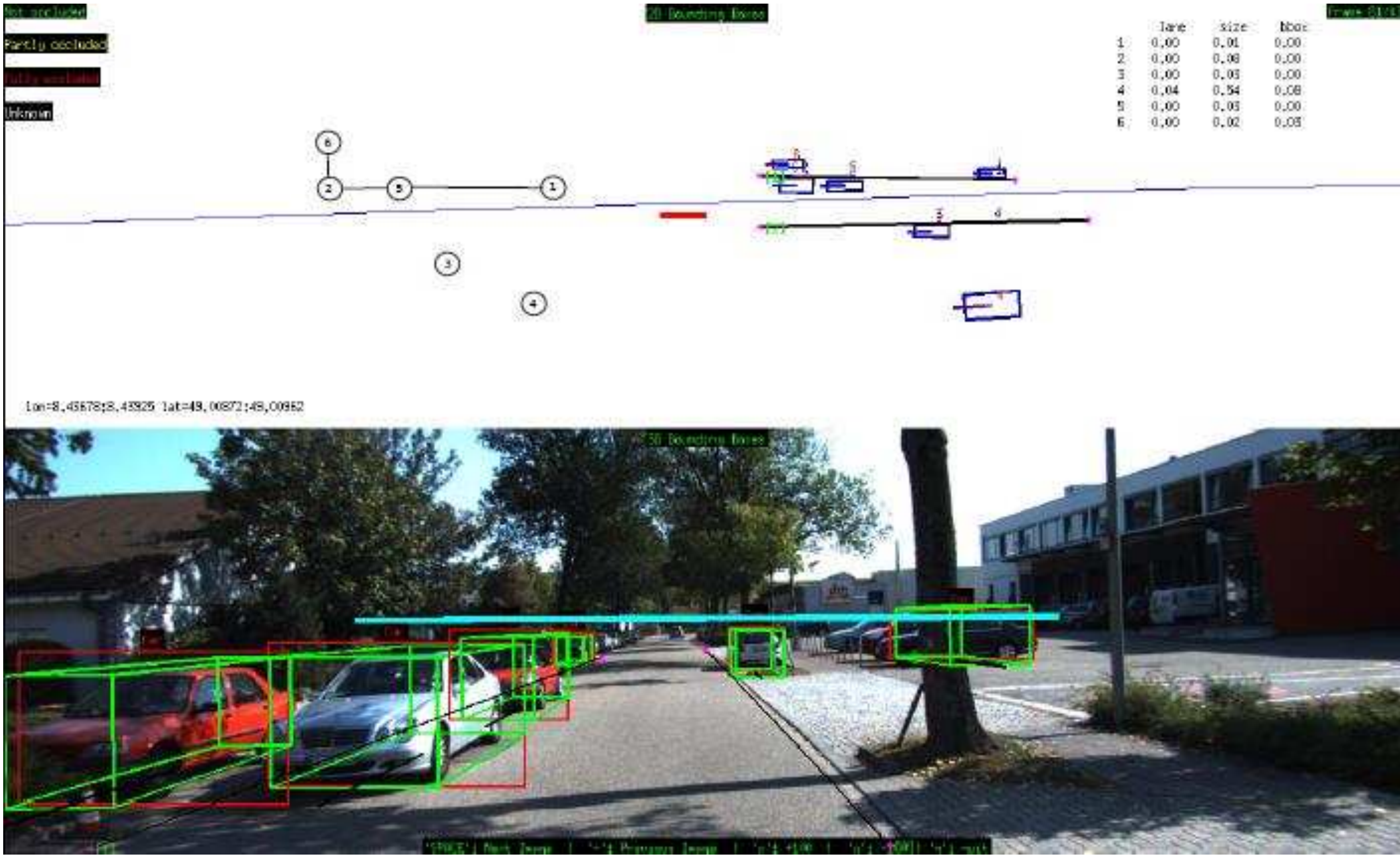
Monocular Road Scene Understanding

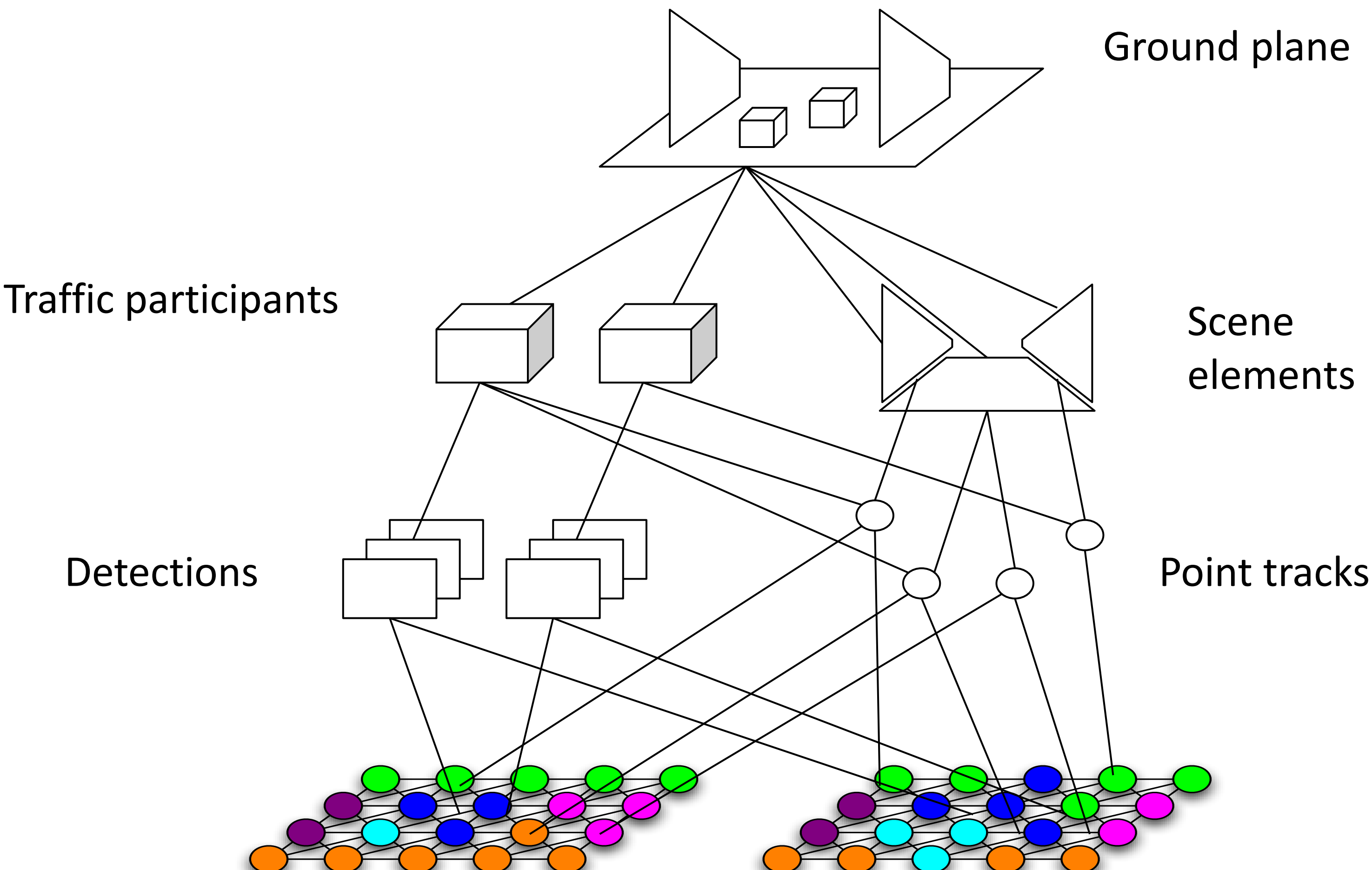


- Object detection: Detect various traffic participants (TP)
- Object localization: position and orientation of TPs in 3D
- Detect various scene elements (SE)
- Enforce relations between TPs and SEs
- Enforce relations between TPs
- Spatially and temporally consistent relationships.

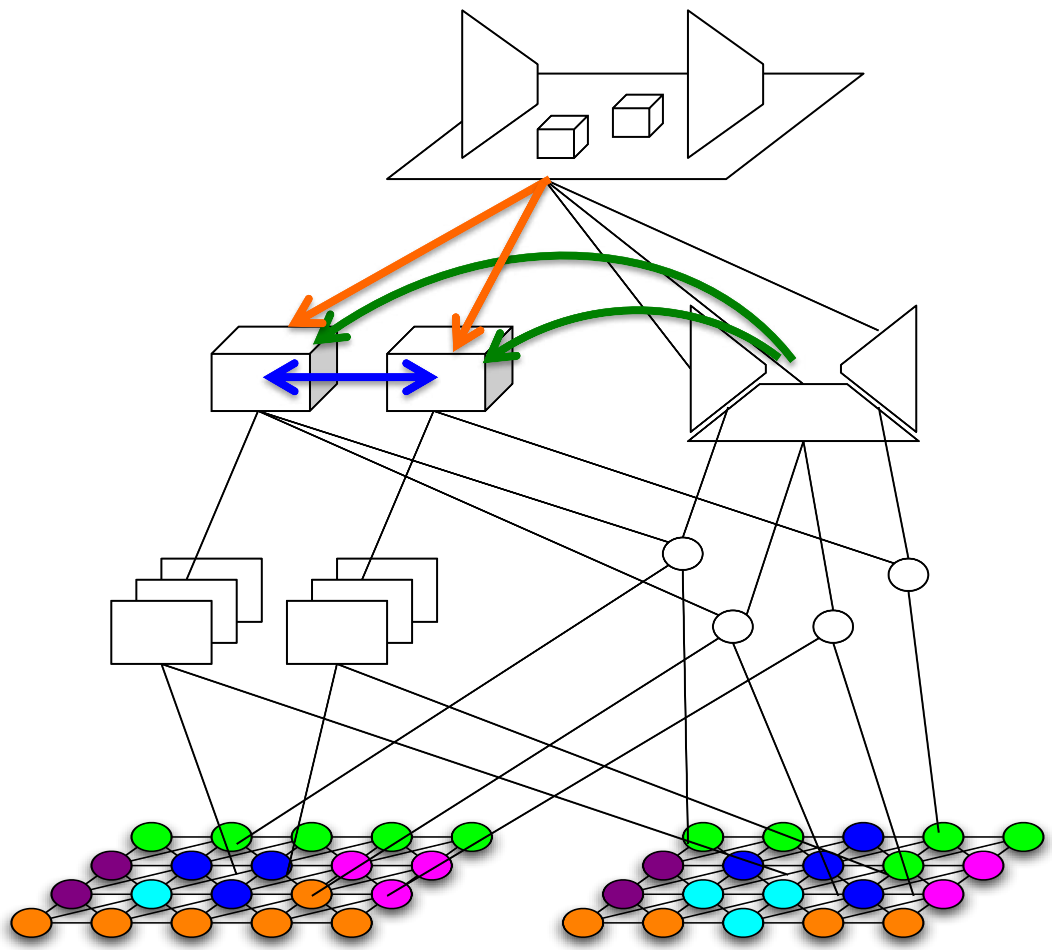
Monocular Road Scene Understanding



Relation to Overall Framework



Relation to Overall Framework



Prior Works

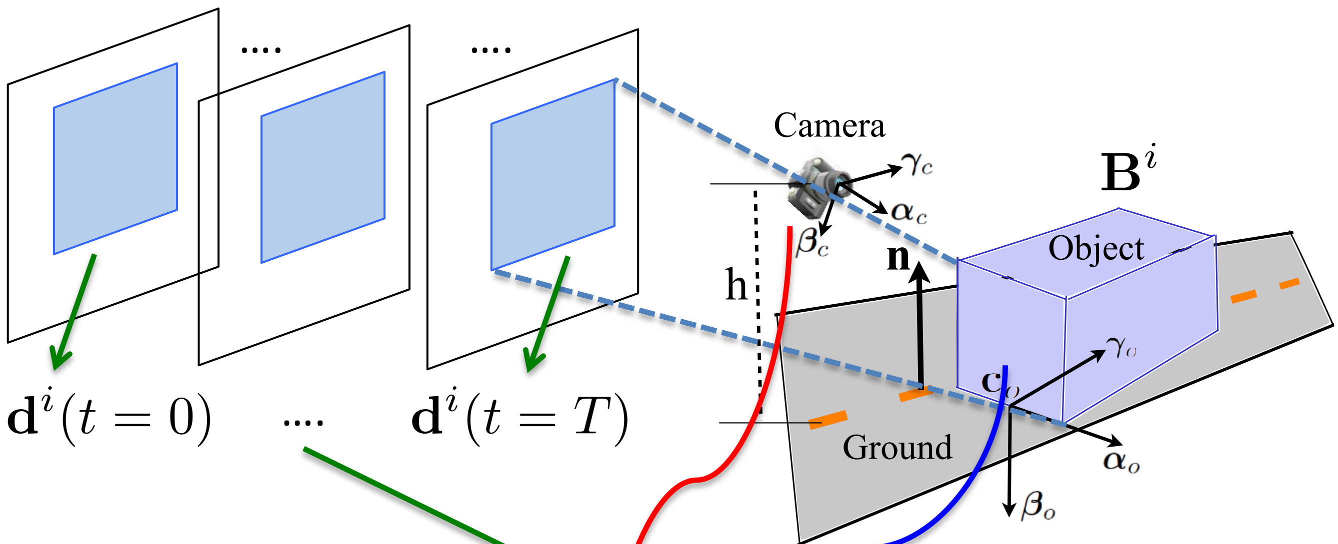
- Localize individual objects
  - [Wojek et al. 2013, Song and Chandraker 2014]
  - Cannot capture interactions
  - We model TP-Scene and TP-TP relationships
- Use stereo
  - [Ess et al. 2011, Geiger et al. 2013]
  - Dense depth information available from stereo
  - We use a single camera (monocular)
- Discontinuous occlusion modeling
  - [Zia et al. 2014]
  - Harder optimization, unpredictable output
  - We develop continuous occlusion models, which yields probabilistically meaningful interactions.

Input-Output

- Inputs:
  - Camera poses and ground plane from SFM
  - 2D object detection
  - Feature tracks on objects
  - GPS
- Outputs:
  - 3D object bounding boxes
  - Consistent TP-Scene relations
    - How objects relate to lane geometry
  - Consistent TP-TP relations
    - Occlusion relationships between objects
    - Which point belongs to which object.

Bounding Box Energy

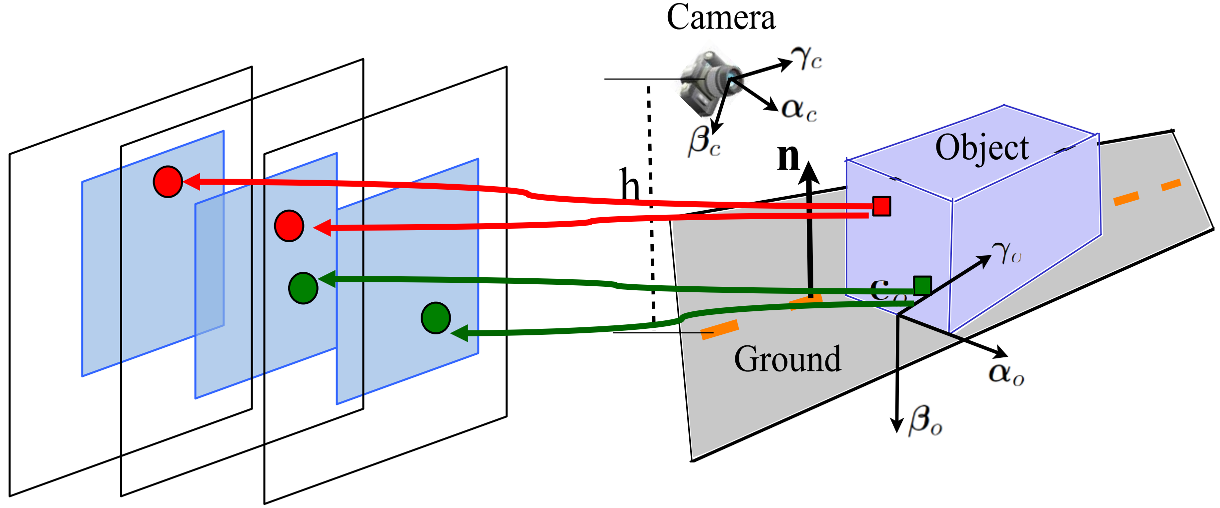
- Simpler version without occlusion
  - Uses prior size, contact of 2D bounding box with ground.



$$E_{bbox} = \|\pi_{\Omega^i(t)}(\mathbf{B}^i) - \mathbf{d}^i(t)\|^2$$

3D Points Energy

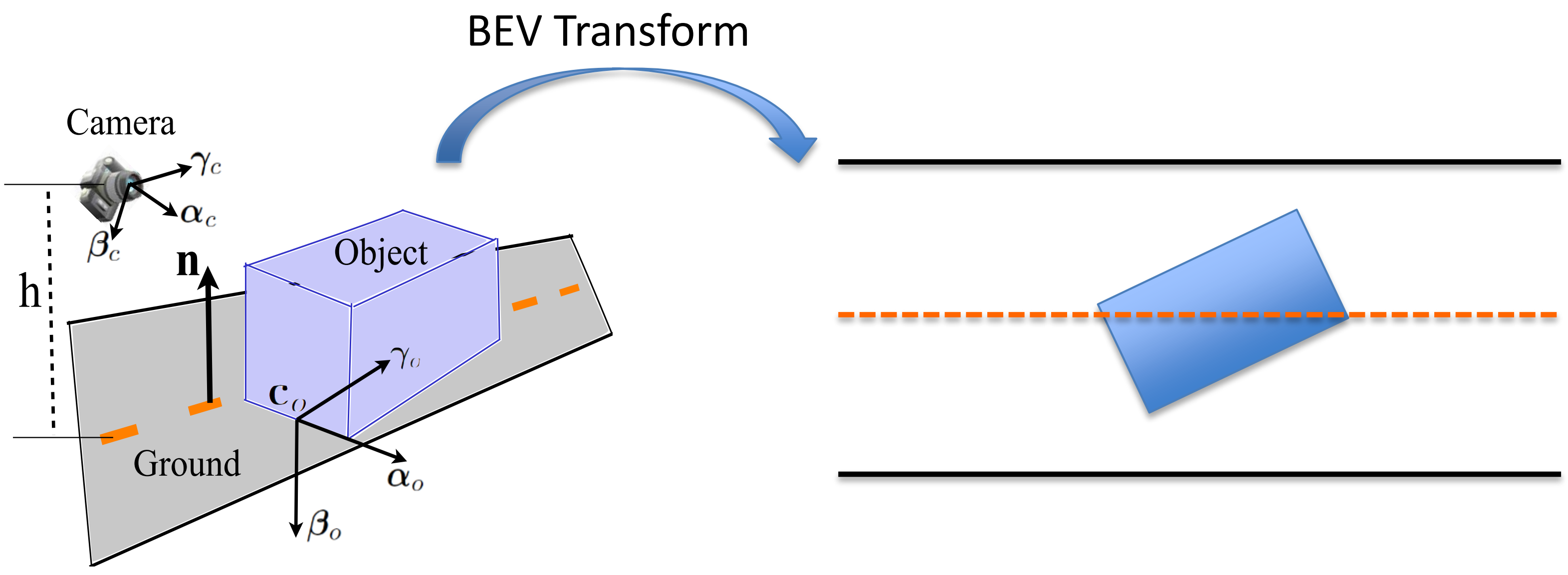
- Simpler version without occlusion
  - Backproject a point at time *t-1* to 3D bounding box
  - Compute reprojection error with observation at time *t*.



$$E_{track} = \sum_{j \in \text{tracks}} \|\mathbf{u}^j(t) - \pi_{\Omega^i(t)}(\pi^{-1}_{\Omega^i(t-1)}(\mathbf{u}_j(t-1)))\|^2$$

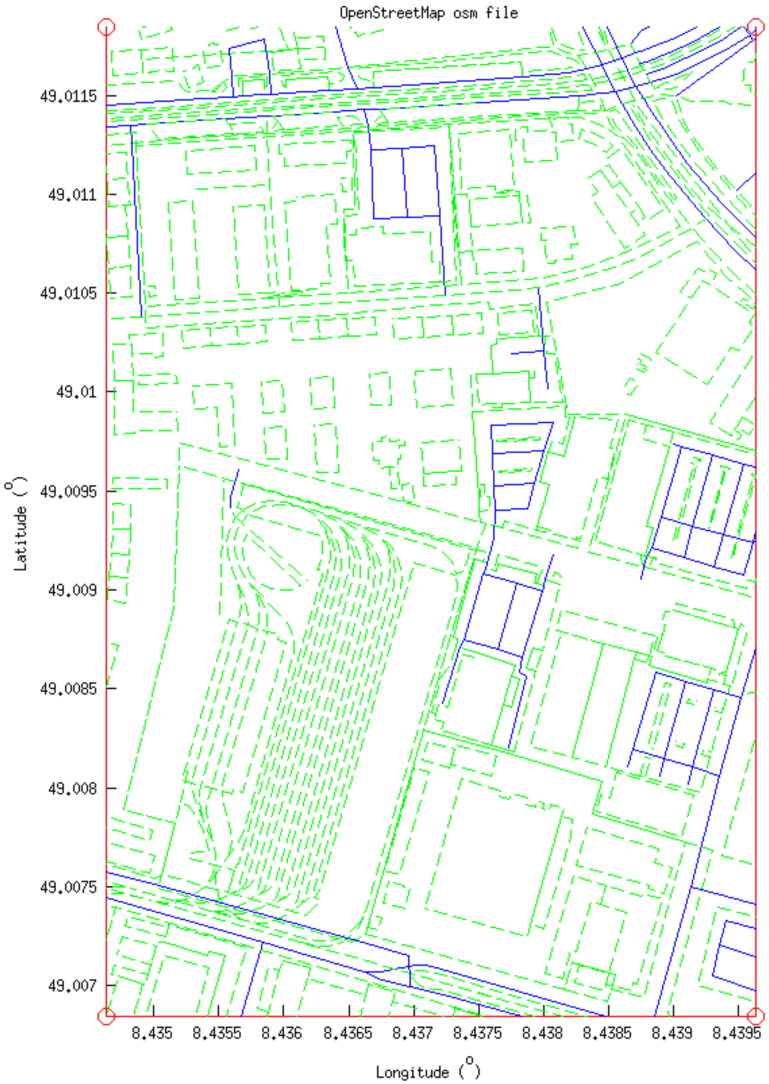
Bird-Eye View

- Use SFM camera pose and ground plane to represent each TP in BEV.



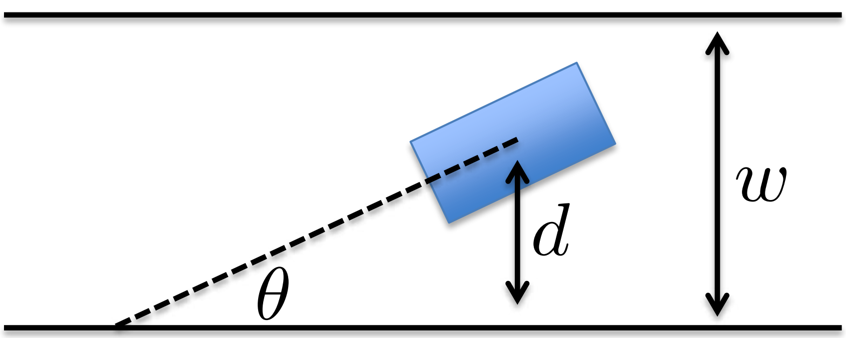
Extracting Scene Elements

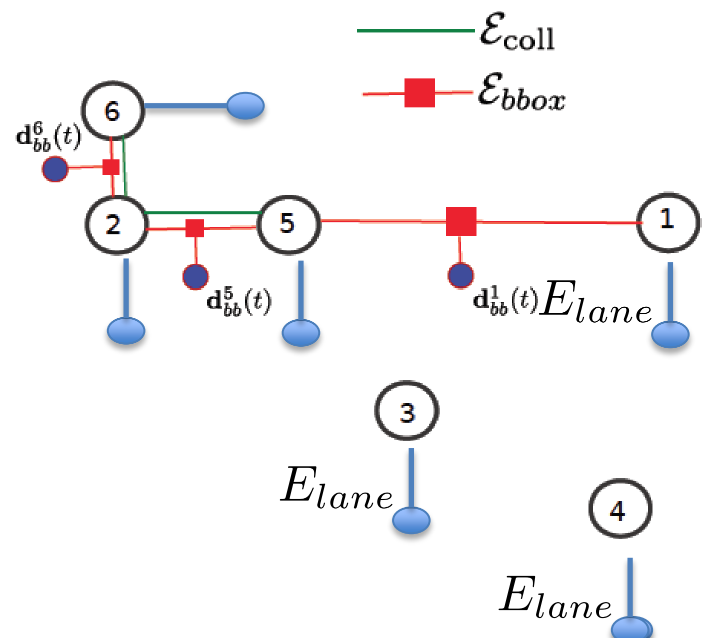
- Use OpenStreetMaps to extract lane geometry
  - Use GPS coordinates
  - Automatically filter out small lanes and side streets
- Annotated lanes (to be replaced by lane detector)
- Align SFM poses with lane geometry.



TP-Scene Constraints

- Lane position and orientation
  - filter away far objects
  - align objects with closest lane directions.

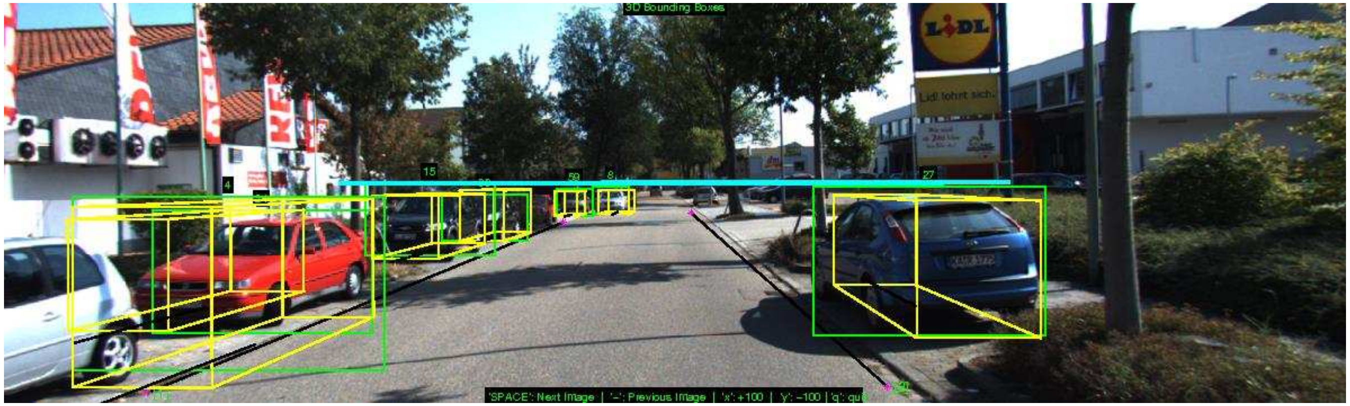


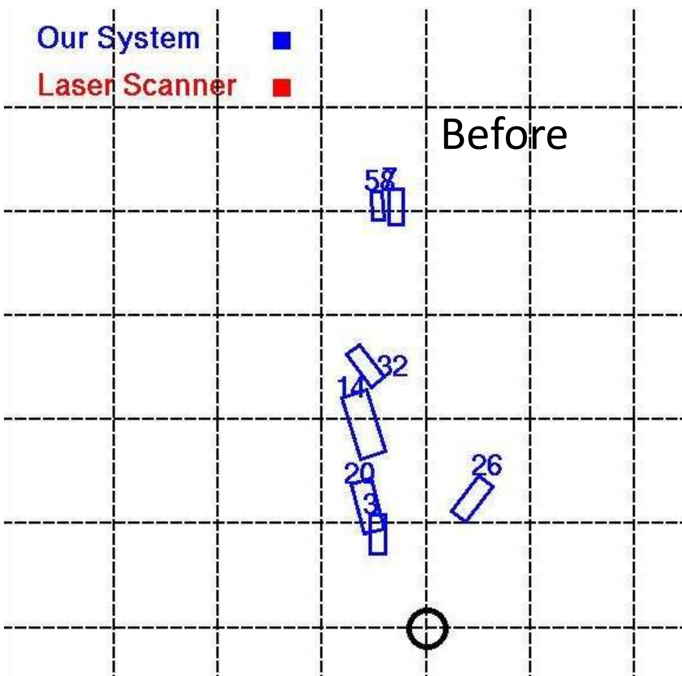


Energy for 1 lane: $\dfrac{1-\cos^2\theta}{1+\exp(-\lambda|w-d|)}$

Soft energy for closest lanes: $E_{lane} = \sum_{k:d_k<\tau} \dfrac{1-\cos^2\theta_k}{1+\exp(-\lambda|w-d_k|)}$

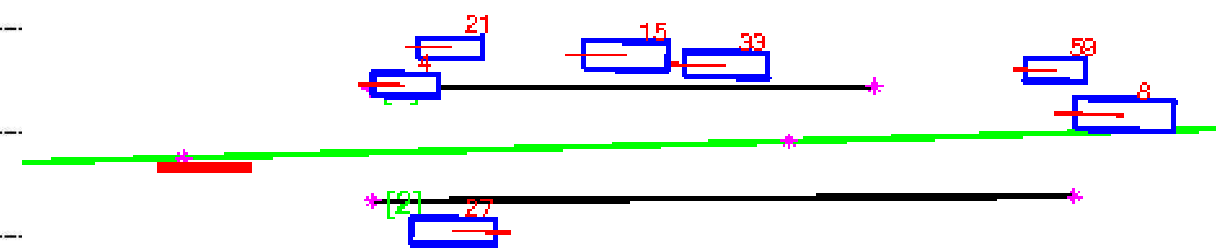
Effect of Lane Energy



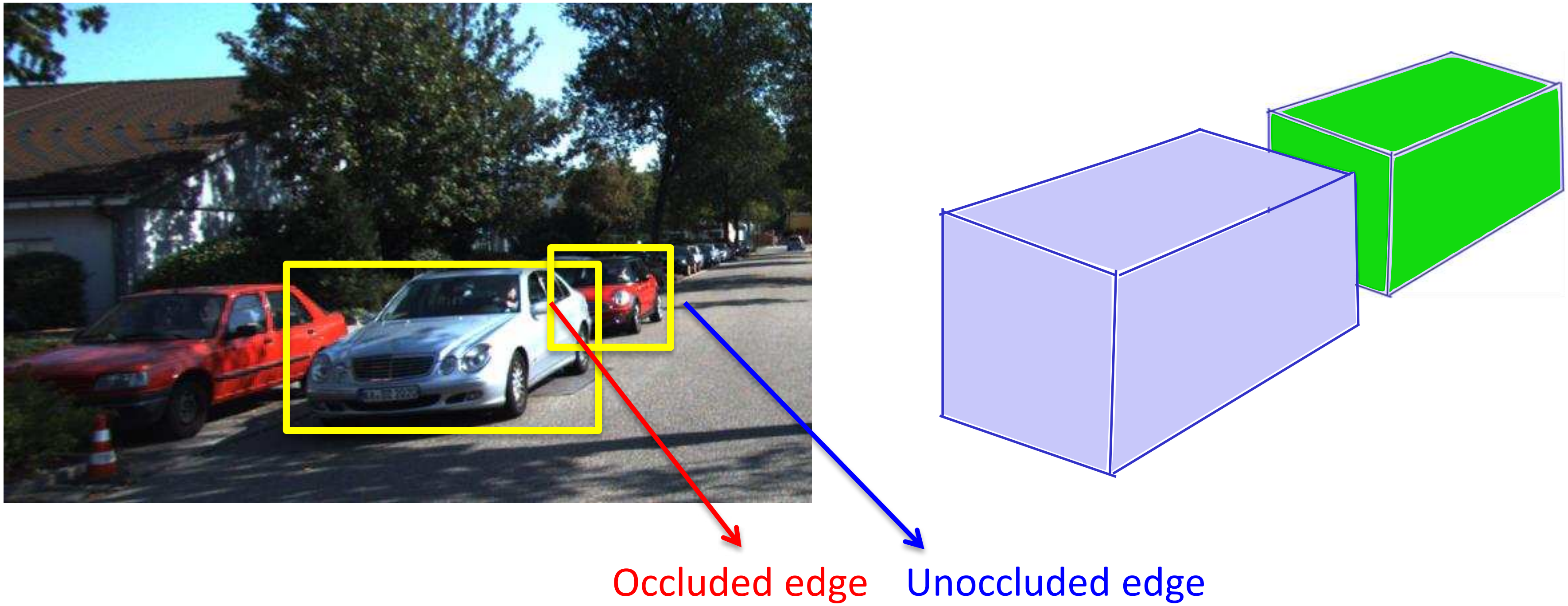


Before

After



TP-TP Relation: Bounding Box Visibility



- Determine 3D bounding boxes aware of occlusions due to objects in front
- Encourage alignment for unoccluded edges
- Relax alignment for occluded edges.

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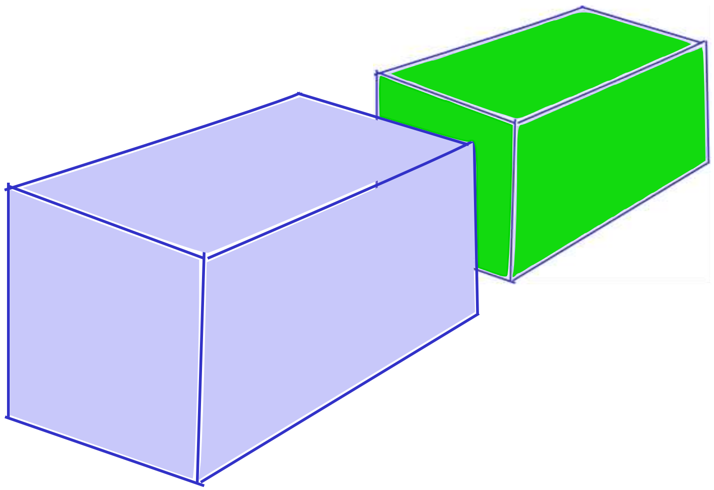

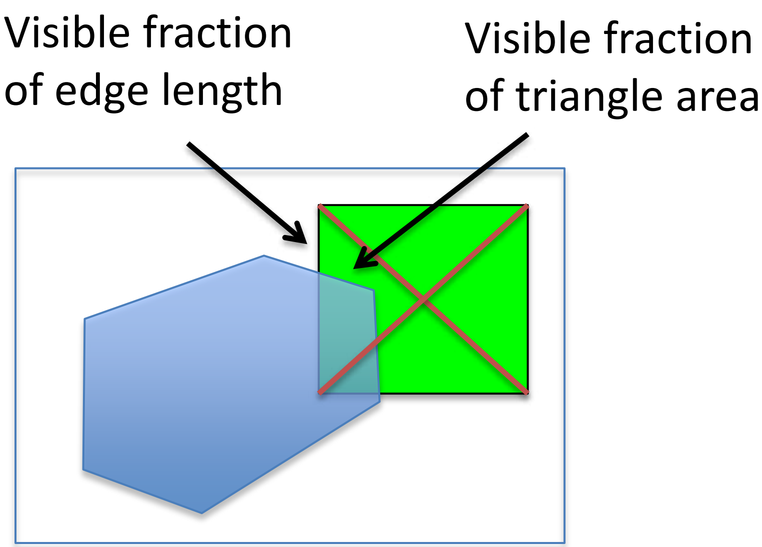

Visibility fraction for a hypothesized bounding box edge: $v^{ij} = \frac{\text{Visible area of triangle}}{\text{Area of triangle}}$

Bounding box energy with occlusion: $E_{bboxOcc} = \sum_{k \in \text{edges}} v_k^{ij} |\pi_{\Omega^j}(\mathbf{B}^j) - \mathbf{d}^j|_k$

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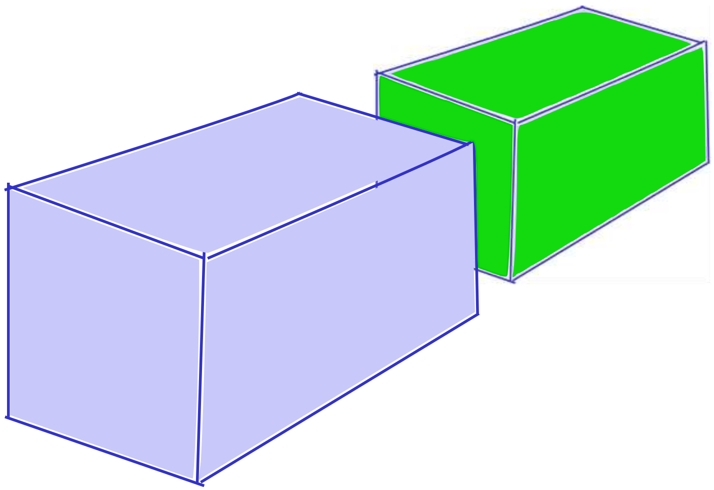

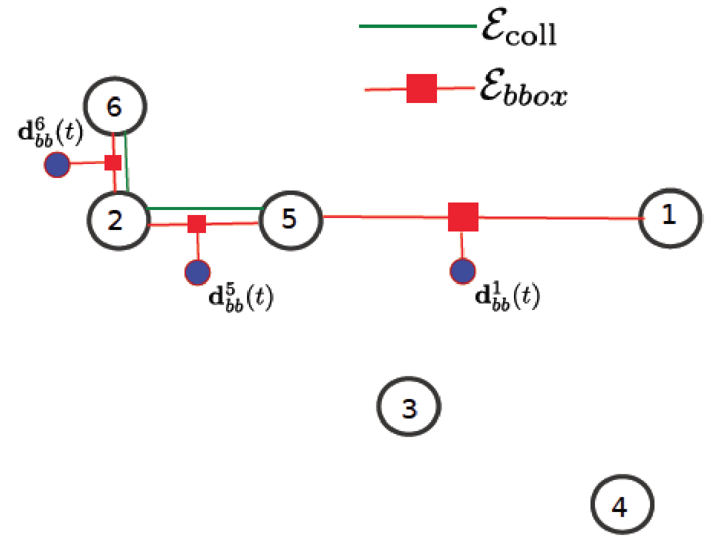

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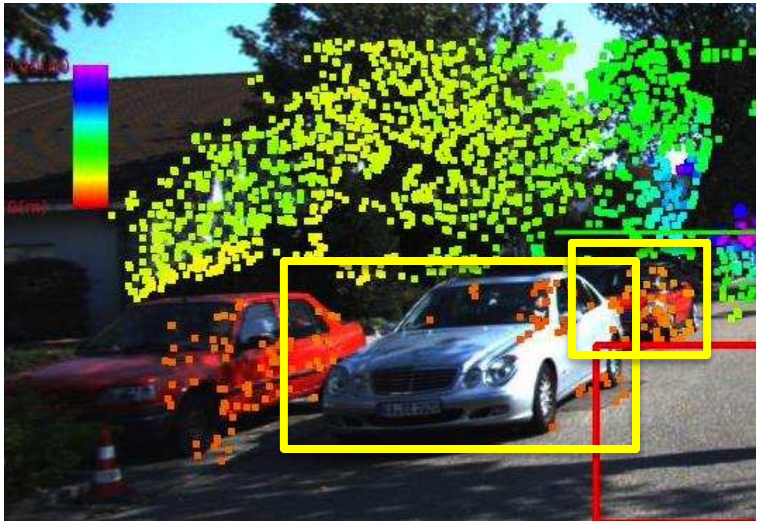
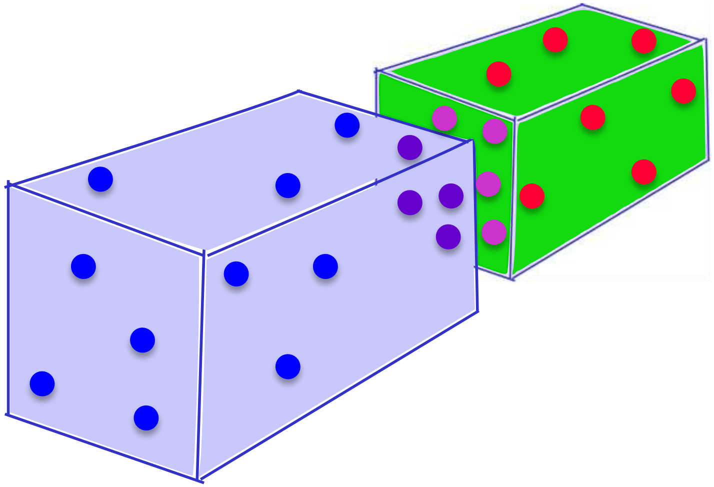
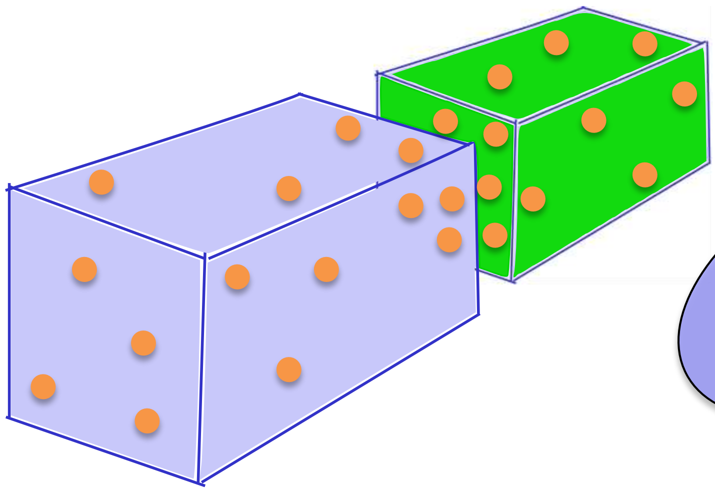
TP-TP: Probabilistic Occlusion

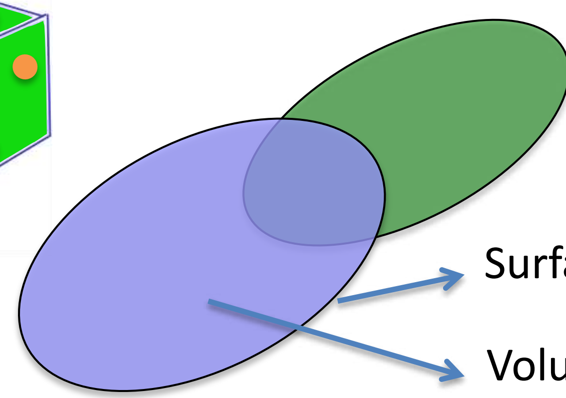




- Determine soft assignment of 2D point tracks to each 3D bounding box
- Probabilistic visibility for each point track.

TP-TP: Probabilistic Occlusion





Represent TPs as translucent 3D ellipsoids

Surface = Reflection (3D Point)

Volume = Transmission
= 1 - Occlusion

Projection of bounding box in image: $[u_l^i, v_t^i, u_r^i, v_b^i] = \pi_{\Omega^i(t)}(\mathbf{B}^i)$

Mean and covariance of ellipsoid: $\mu_i = \frac{1}{2}\begin{bmatrix} u_l^i + u_r^i \\ v_t^i + v_b^i \end{bmatrix} \quad \Sigma_i = \begin{bmatrix} \frac{2}{(u_l^i - u_r^i)^2} & 0 \\ 0 & \frac{2}{(v_t^i - v_b^i)^2} \end{bmatrix}$

Model occlusion as a continuous soft probability:

$$f_{\text{occ}}^i(u, v, \lambda) = \frac{N(u, v; \mu_i, \Sigma_i)}{1 + e^{-\frac{\lambda - \mu_i^{(d)}}{\beta}}} \text{where } \mu_d = \Omega^i(t)_z$$

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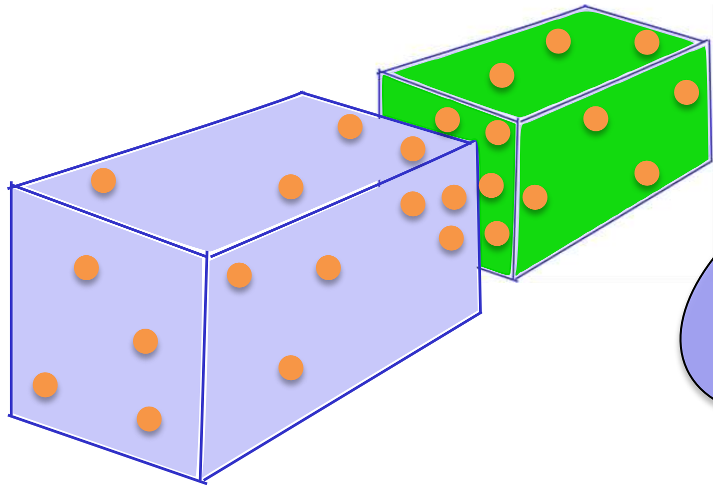

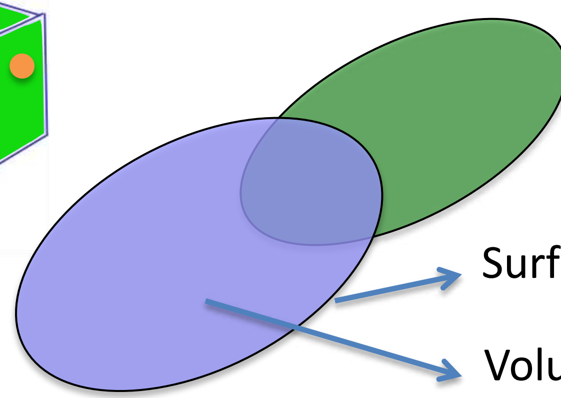

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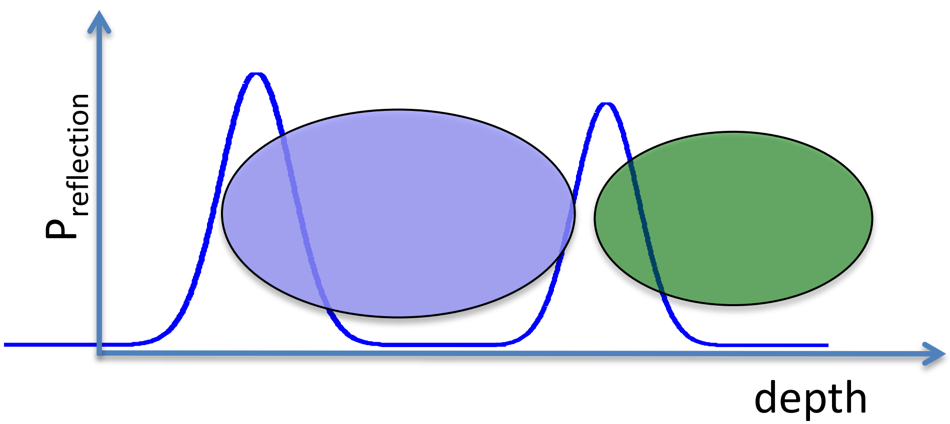
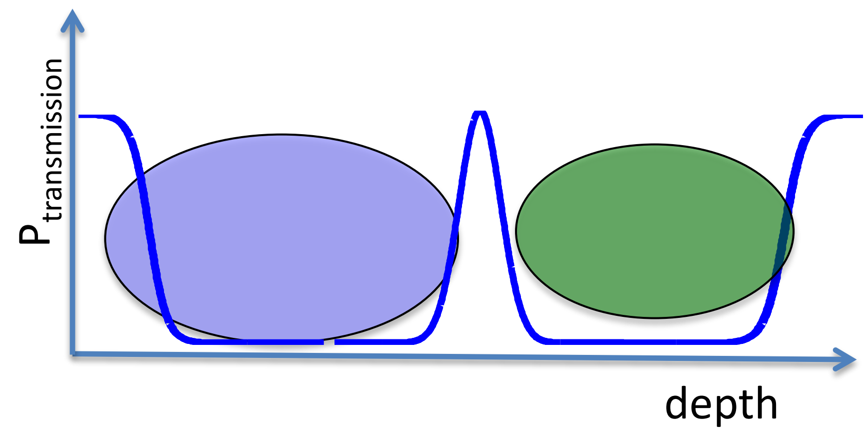
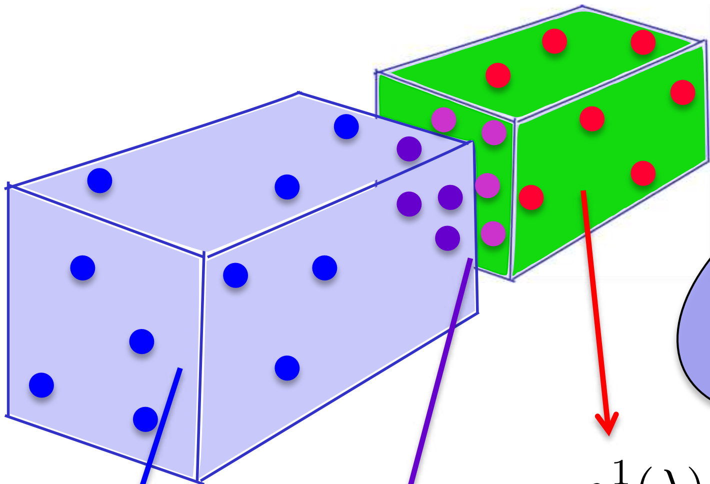




Association probability for point j with object i : $a^{ij}(\lambda) = P^{i}_{refl} \prod_{0}^{\lambda} P^{d\lambda}_{trans}$

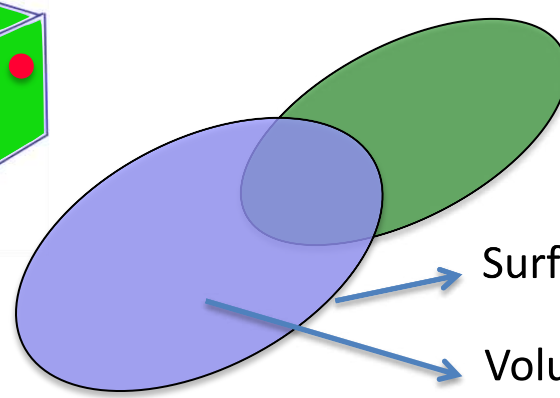
TP-TP: Probabilistic Occlusion



$a^1(\lambda) \to 0$
$a^2(\lambda) \to 1$

$a^1(\lambda) \approx 0.5$
$a^2(\lambda) \approx 0.5$

$a^1(\lambda) \to 1$
$a^2(\lambda) \to 0$



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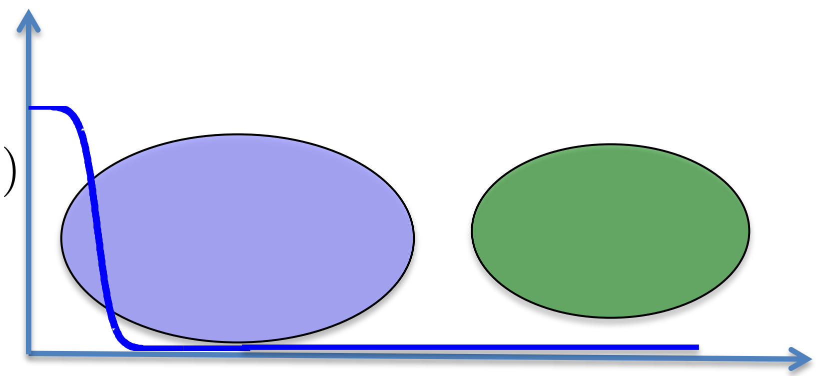

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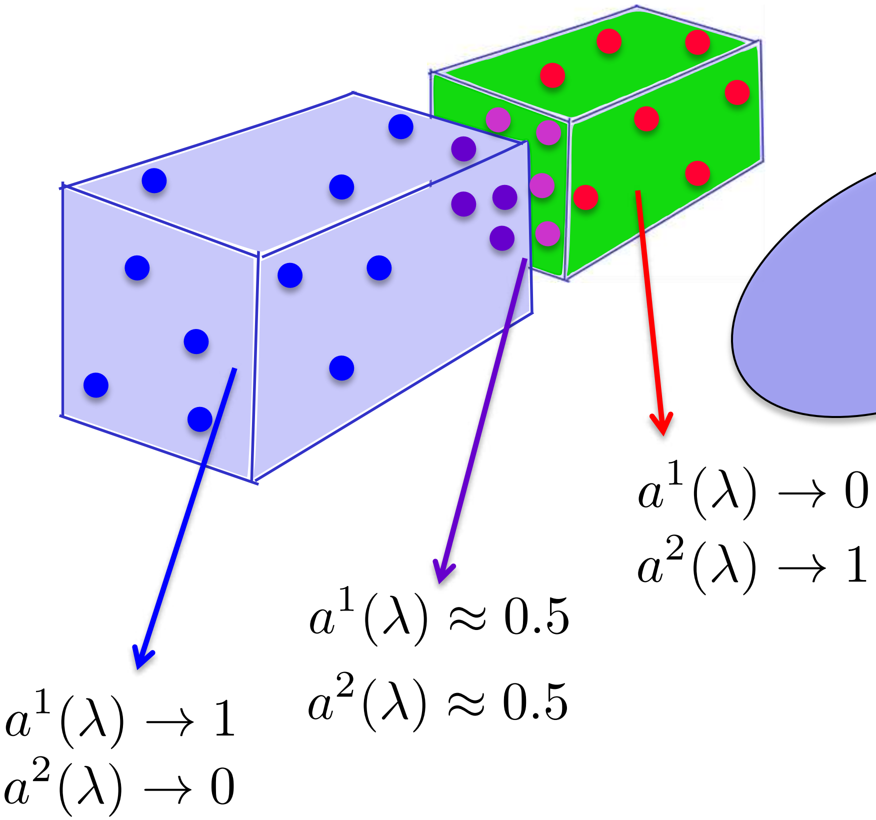
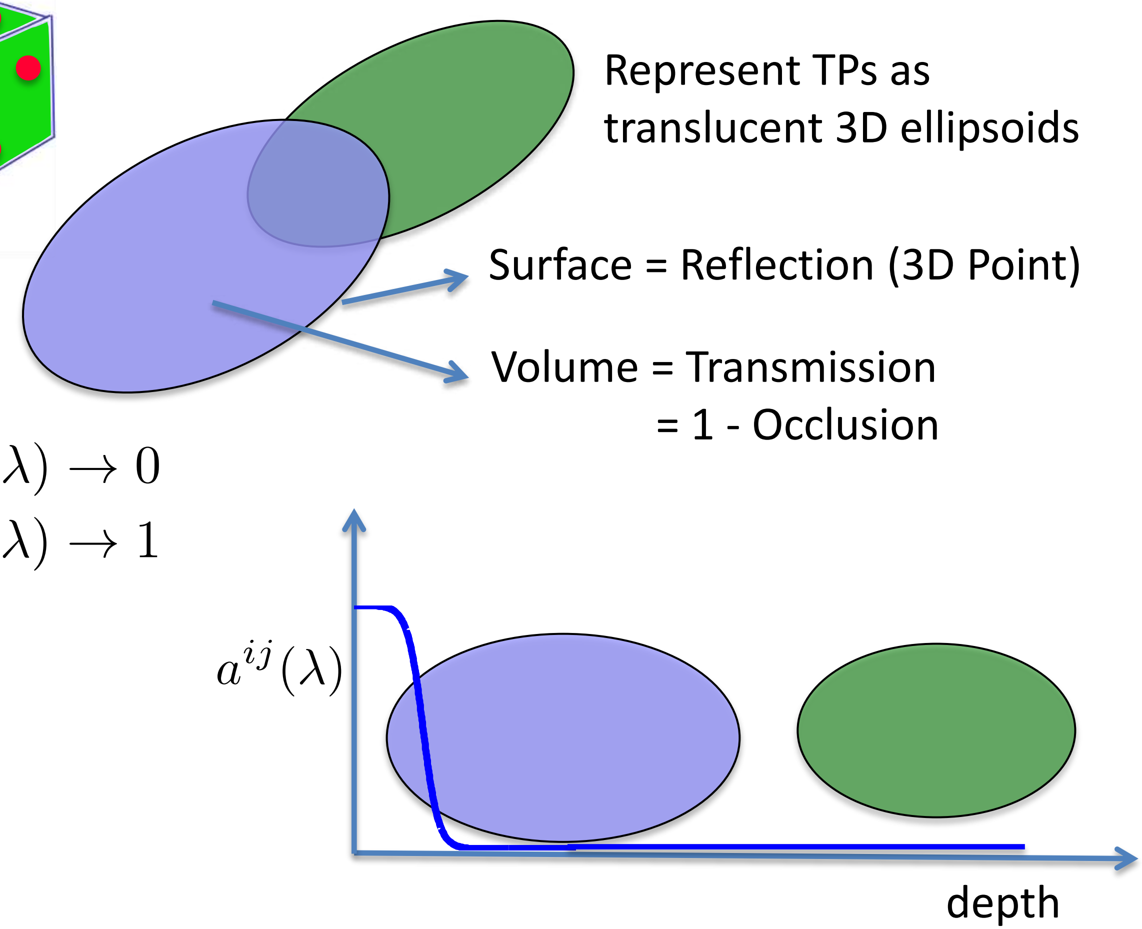




Point track energy considering TP-TP occlusions:

$$E_{trackOcc} = \sum_{i \in \text{objects}} \sum_{j \in \text{tracks}} a^{ij} \| \mathbf{u}^j(t) - \pi_{\Omega^i(t)}(\pi^{-1}_{\Omega^i(t-1)}(\mathbf{u}_j(t-1))) \|^2$$

Probabilistic Occlusion Levels

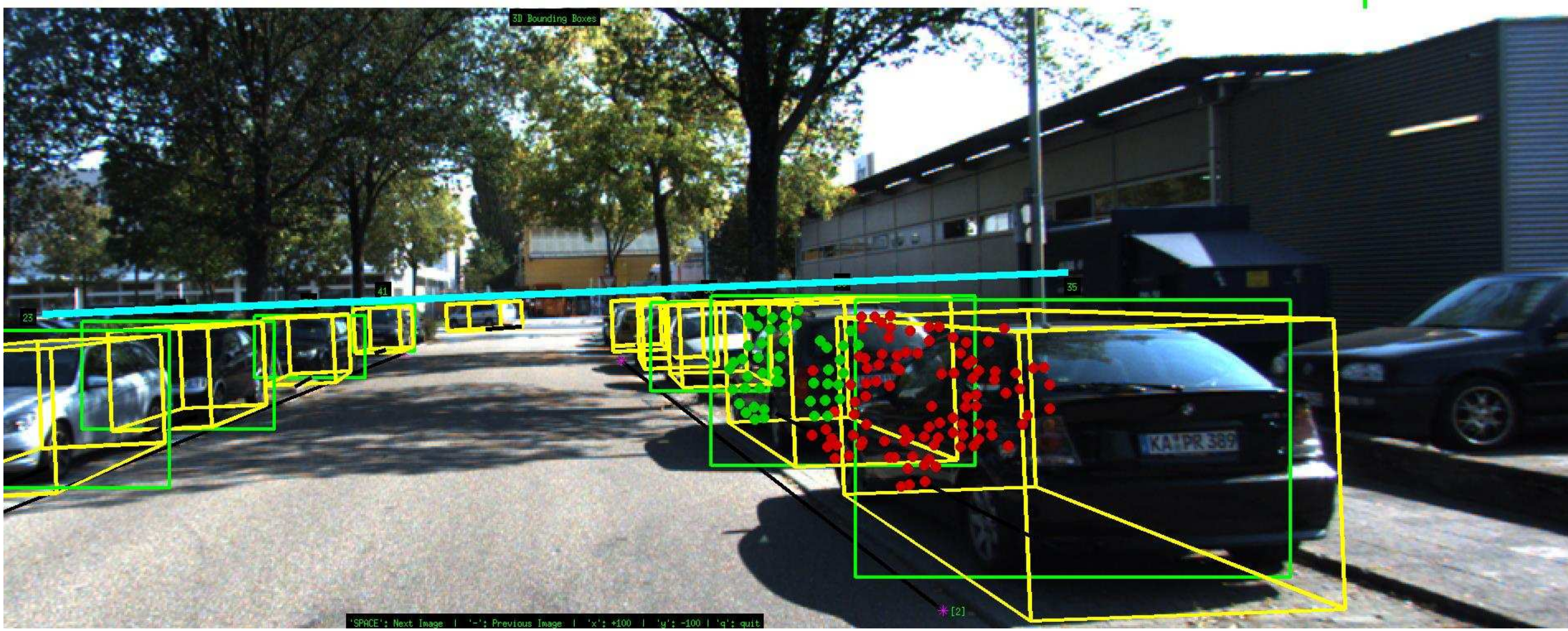
Not occluded

Partly occluded

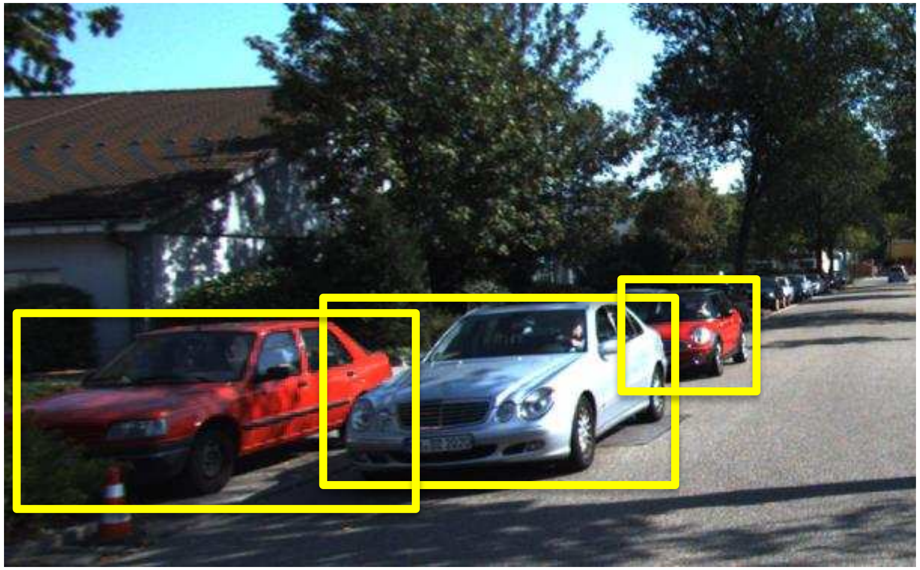
Mostly occluded

- Probabilistic specification of occlusion level for each object

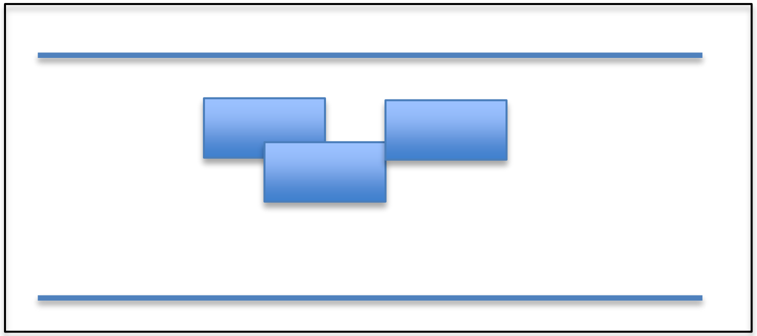
Effect of Occlusion Energy



TP-TP Relationships: Collision

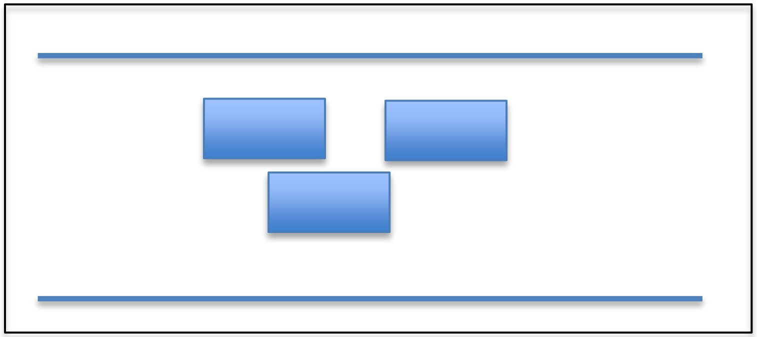


BEV Localization



Objects cannot physically occupy the same 3D space.

Collision Resolution



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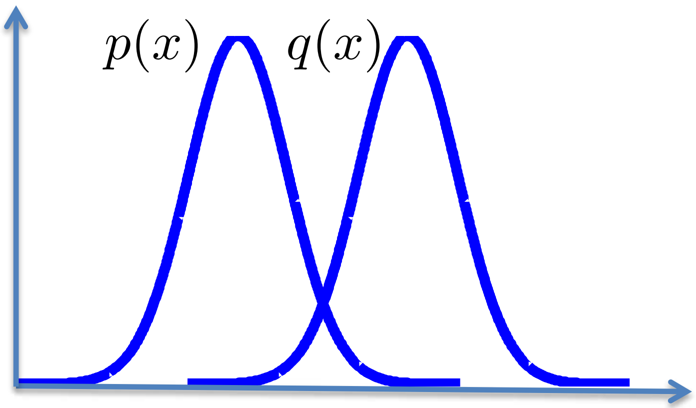
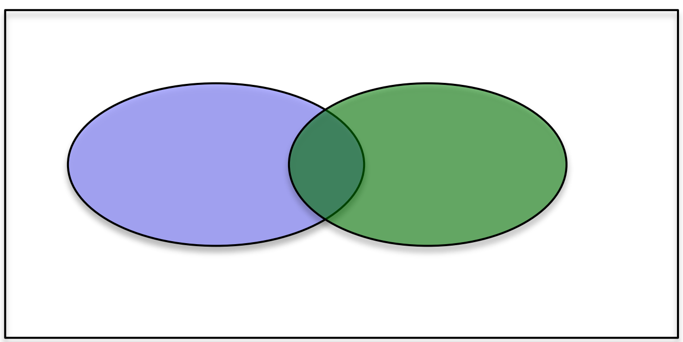
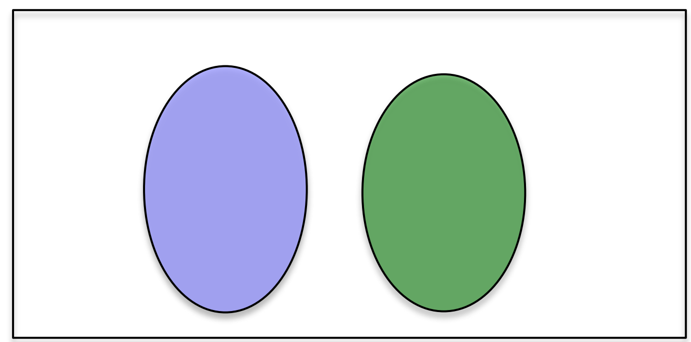


Bhattacharya coefficient for distance:

$$BC(p,q) = \int_0^{\infty} \sqrt{p(x)q(x)}\, dx$$

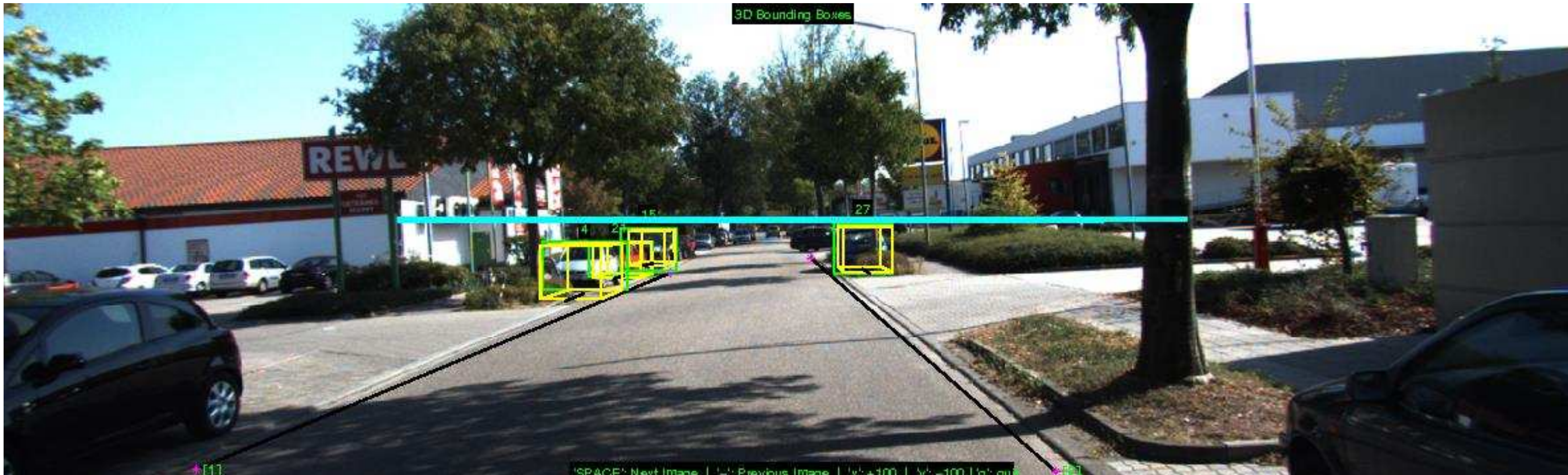
Has analytic form for Gaussian distributions.

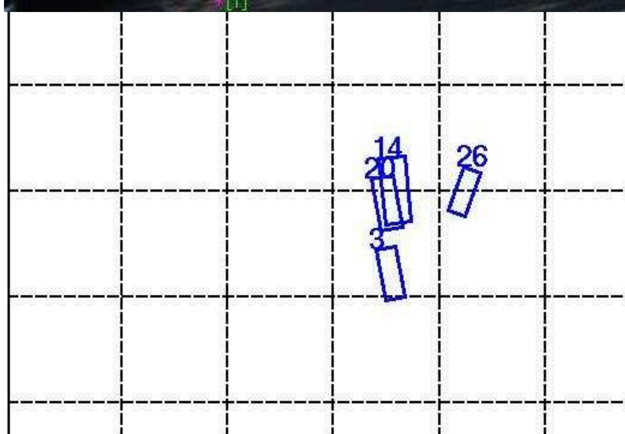




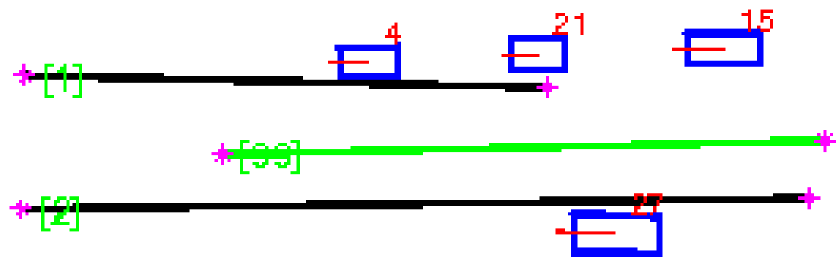
$$\mathcal{E}_{\mathrm{col}}^{ijt} = \frac{|\Sigma_i|^{\frac{1}{4}}|\Sigma_j|^{\frac{1}{4}}}{|\frac{1}{2}\Sigma_i + \frac{1}{2}\Sigma_j|^{\frac{1}{2}}} e^{-\frac{1}{8}\left(\mathbf{p}^{(i)}(t)-\mathbf{p}^{(i)}(t)\right)^\top \left(\frac{1}{2}\Sigma_i+\frac{1}{2}\Sigma_j\right)^{-1}\left(\mathbf{p}^{(i)}(t)-\mathbf{p}^{(i)}(t)\right)}$$

Effect of Collision Energy



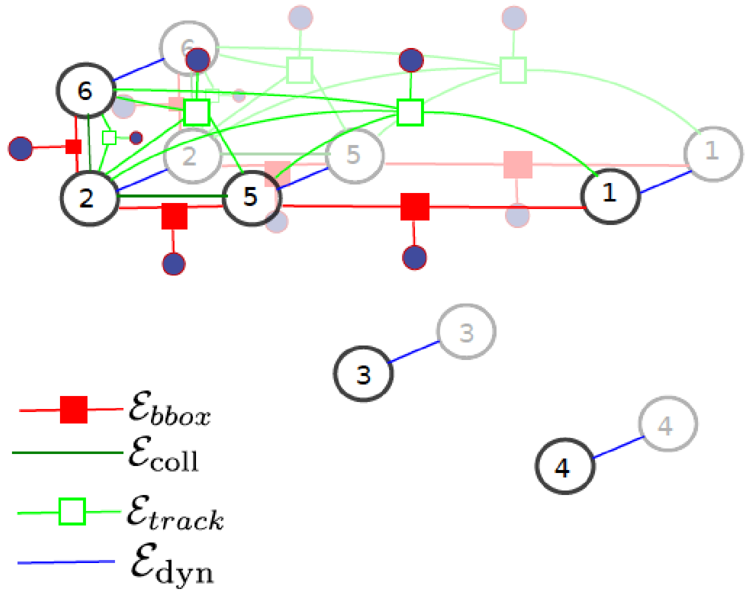


Before



After

Temporal Consistency



- Dynamic terms
  - holonomic, orientation and velocity constraints.

$$\mathcal{E}^{it}_{\text{dyn-hol}} = 1 - \omega^{(i)}(t-1) \cdot (\mathbf{p}^{(i)}(t) - \mathbf{p}^{(i)}(t-1))$$

Car moves only in forward direction

$$\mathcal{E}^{it}_{\text{dyn-ori}} = \|\omega^{(i)}(t) - \omega^{(i)}(t-1)\|^2$$

Smoothness for orientation

$$\mathcal{E}^{it}_{\text{dyn-vel}} = \|(\mathbf{p}^{(i)}(t) - 2\mathbf{p}^{(i)}(t-1)) + \mathbf{p}^{(i)}(t-2)\|^2$$

Constant velocity

Inference

- Just use unconstrained minimization for now
- Alternatingly minimize for a few iterations:
  - Lane + Dynamic energies
  - Bounding box + Size energies
  - Occlusion + Collision energies

- Future work:
  - Message passing to exploit graph structure.

Results

- Dataset : sequences from KITTI
- Metrics :
  - Translation error
  - Orientation error (yaw angle along ground plane)
  - Size error (averaged over length, width and height)
  - Position error in Z (depth)
  - Position error in X (lateral)

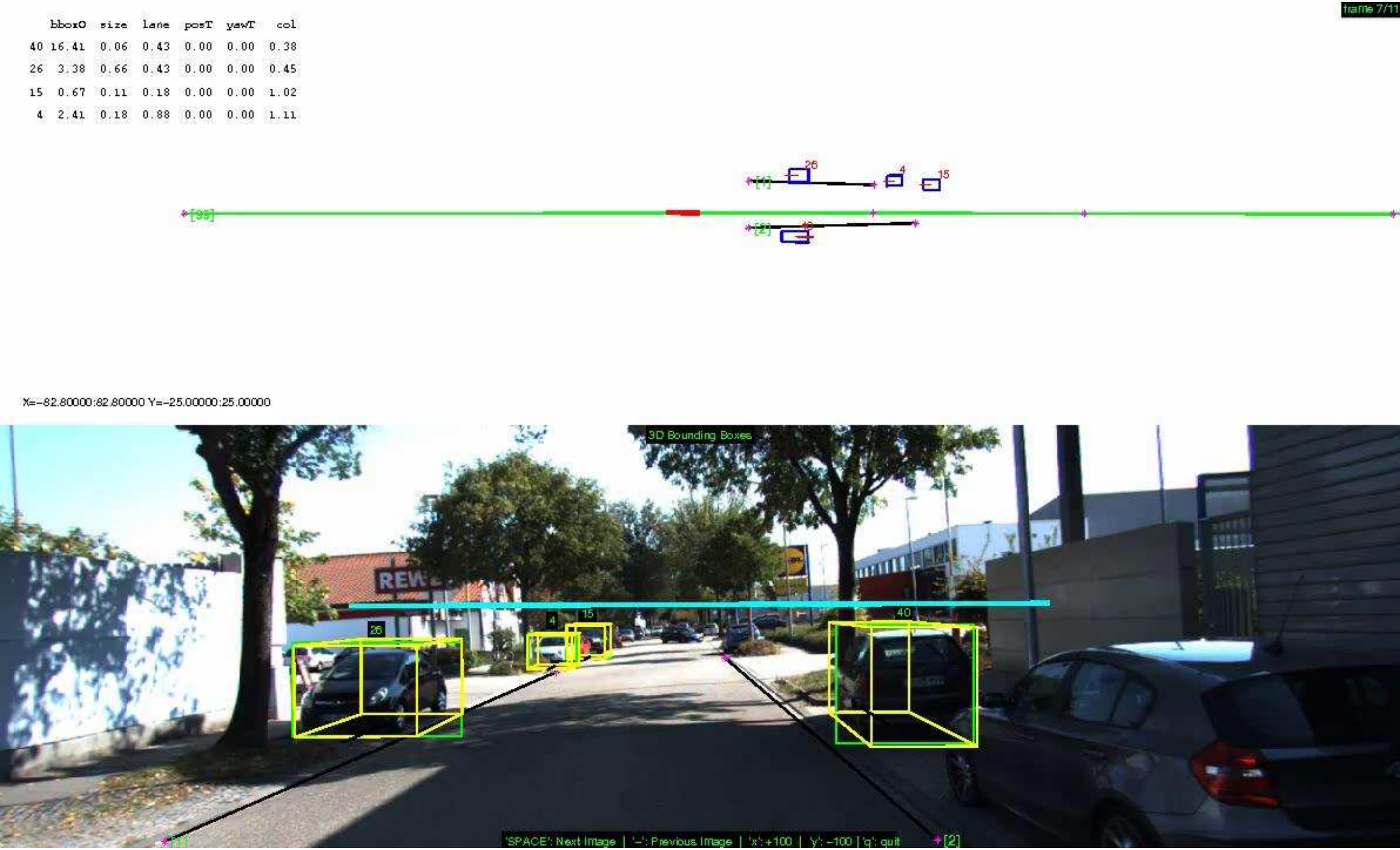
Results

	Translation (%)	Yaw (Degrees)	Size (%)	Z (%)	X (%)
Independent Localization	8.210	19.824	**1.209**	7.922	**1.469**
Bounding Box + Lane	7.761	4.787	1.283	7.358	1.689
Bounding Box + Lane + Dynamic	7.704	**4.635**	1.264	7.294	1.660
Occlusion + Lane + Dynamic	**7.697**	4.764	1.264	**7.285**	1.661
Occlusion + Lane + Dynamic + Collision	7.802	4.655	1.259	7.362	1.727

- Errors decrease using scene and TP constraints
  - Scene elements constrain object orientation (yaw)
  - Also better translation and depth errors

Videos

	bboxO	size	lane	posT	yawT	col
40	16.41	0.06	0.43	0.00	0.00	0.38
26	3.38	0.66	0.43	0.00	0.00	0.45
15	0.67	0.11	0.18	0.00	0.00	1.02
4	2.41	0.18	0.88	0.00	0.00	1.11



Conclusions

- TP-Scene interactions lead to better localization
  - Significant improvement in orientation accuracy
- Modeling TP-TP interactions lends consistency
  - Probabilistically reason about occlusions
  - 3D object localization incorporating visibility
  - Soft point track associations to handle occlusions
  - Resolve collisions
- Better accuracy than independent localization
  - For "important" metrics (depth and orientation)
- Probabilistic notion of TP-Scene and TP-TP interactions
  - Forms input to scene recognition applications.

Future Work

- Learning the weights
- Better optimization
- More extensive evaluation.