SqueezeSeg: Convolutional Neural Nets with Recurrent CRF for Real-Time Road-Object Segmentation from 3D LiDAR Point Cloud

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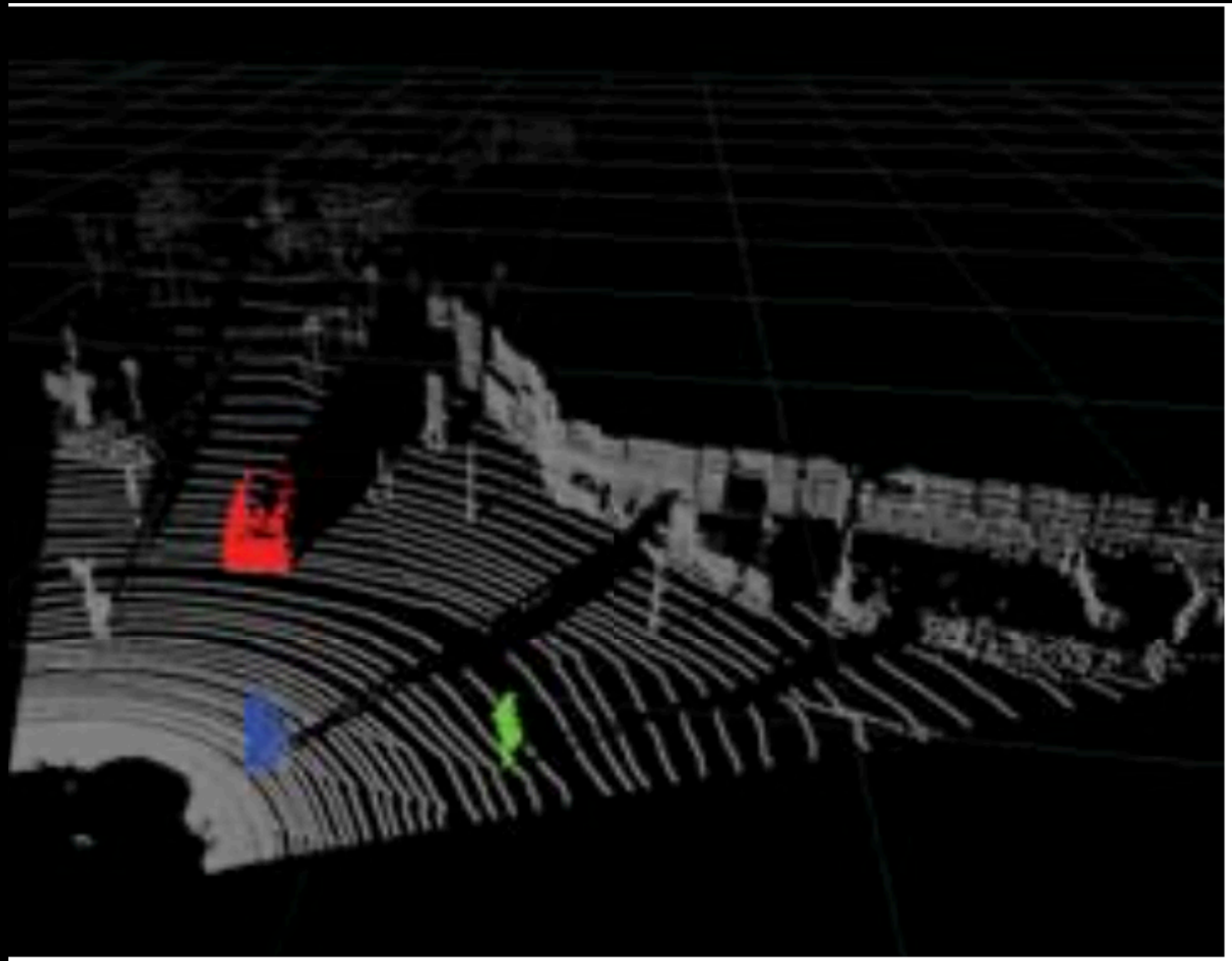
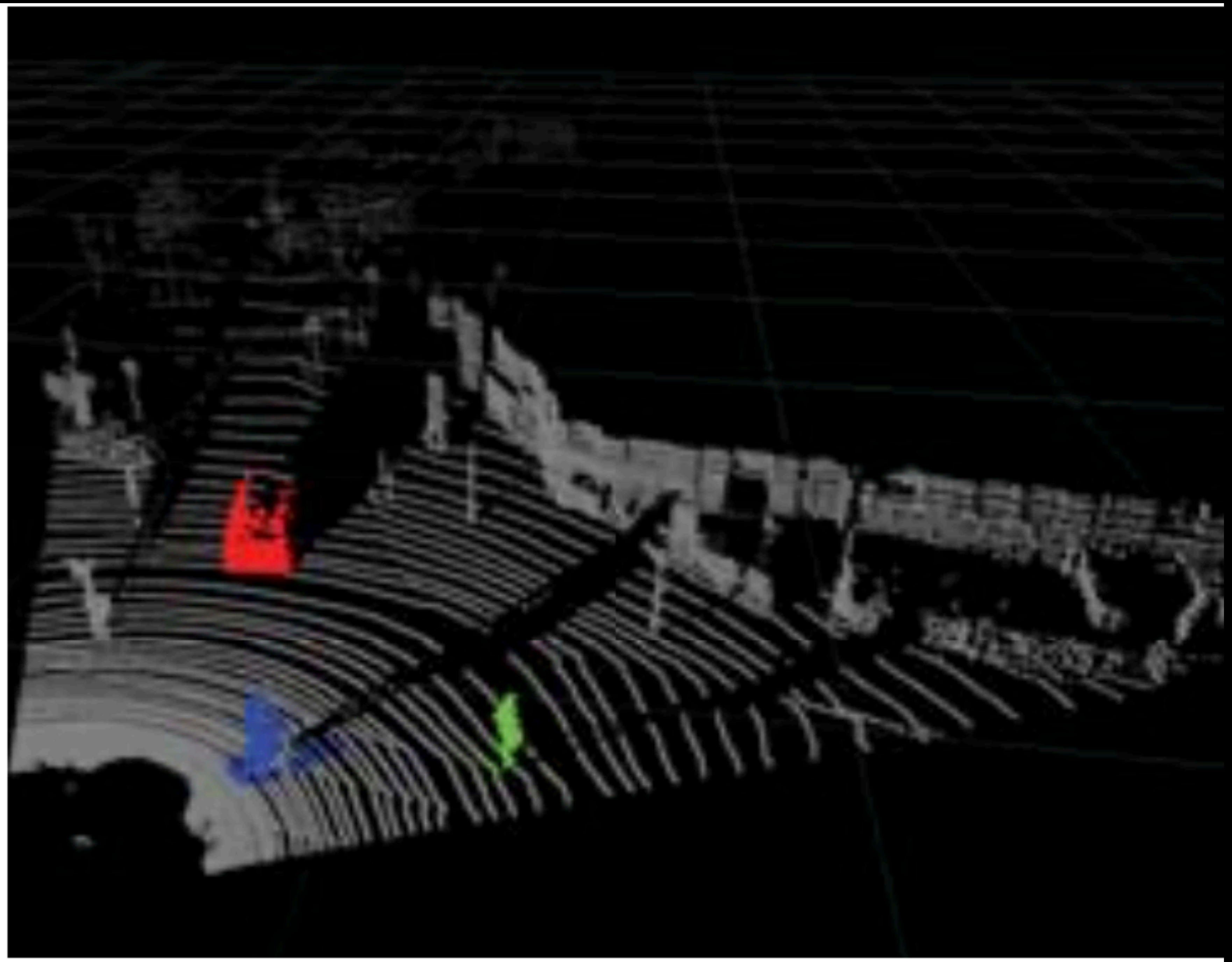
Introduction

Address semantic segmentation of road-objects from 3D LiDAR point clouds. In particular, we wish to detect and categorize instances of interest, such as cars, pedestrians and cyclists.



Ground truth segmentation



Predicted segmentation

RELATED WORK

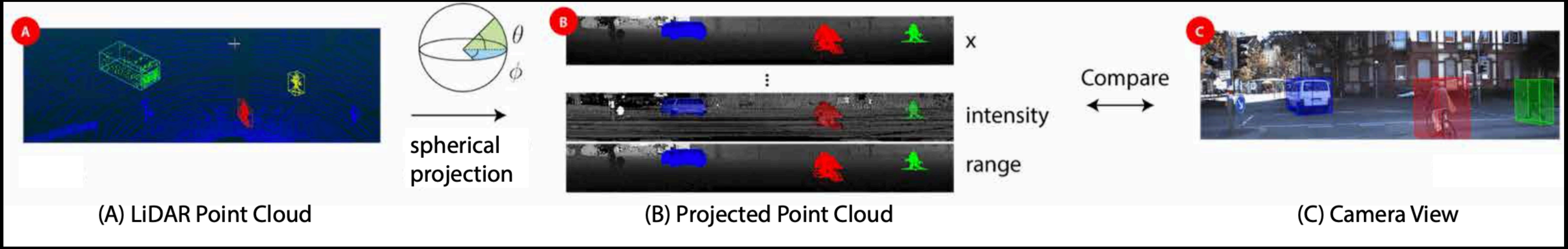
- Semantic segmentation for 3D LiDAR point clouds
- CNN for 3D point clouds
- Semantic Segmentation for Images
- Data Collection through Simulation

METHOD DESCRIPTION

Point Cloud Transformation

$$\theta = \arcsin \frac{z}{\sqrt{x^2+y^2+z^2}}, \quad \tilde{\theta} = \lfloor \theta / \triangle\theta \rfloor,$$
$$\phi = \arcsin \frac{y}{\sqrt{x^2+y^2}}, \quad \tilde{\phi} = \lfloor \phi / \triangle\phi \rfloor.$$

project the LiDAR point cloud onto a sphere for a dense, grid-based representation



METHOD DESCRIPTION

Network structure

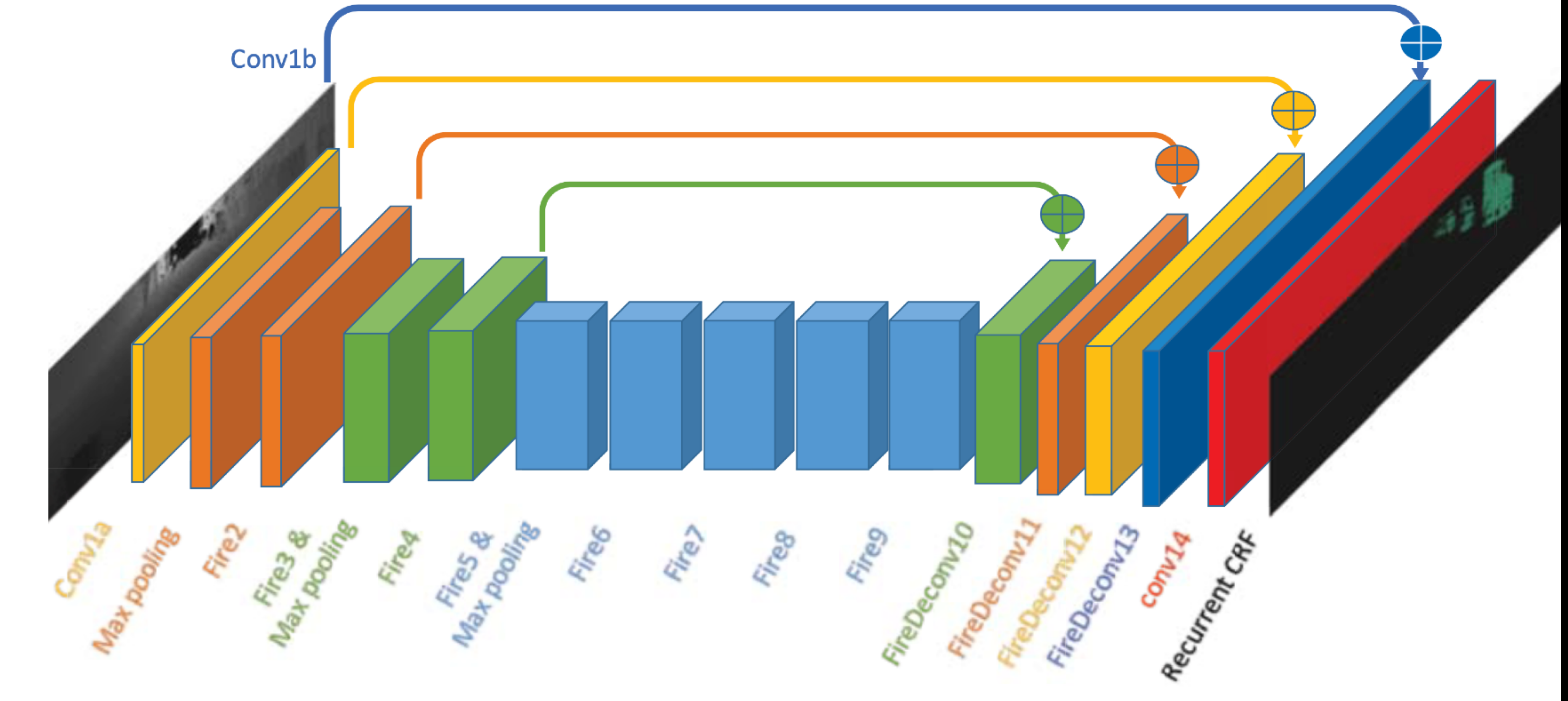
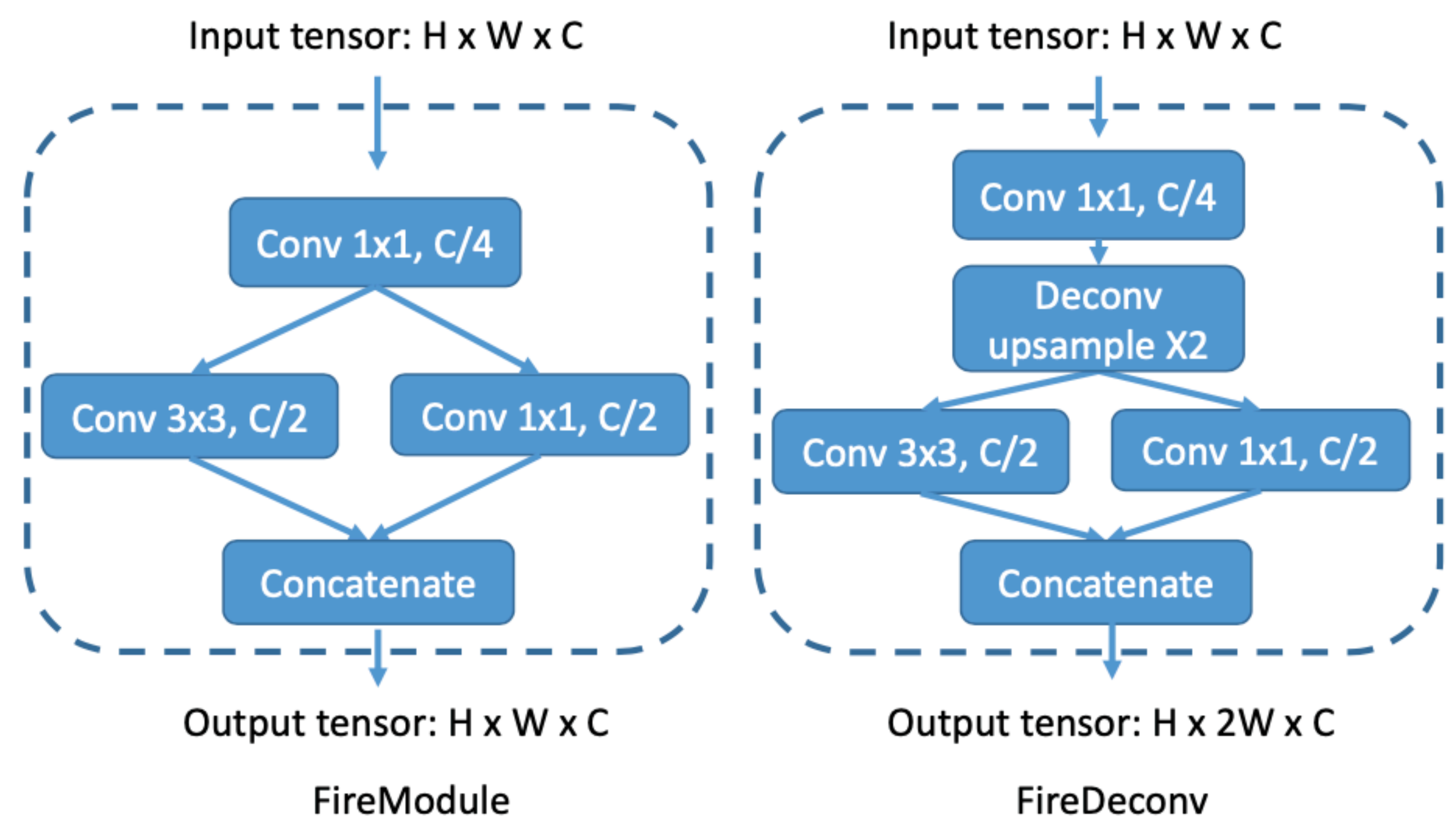


Fig. 3: Network structure of SqueezeSeg.



METHOD DESCRIPTION

Conditional Random Field

Energy function of CRF model

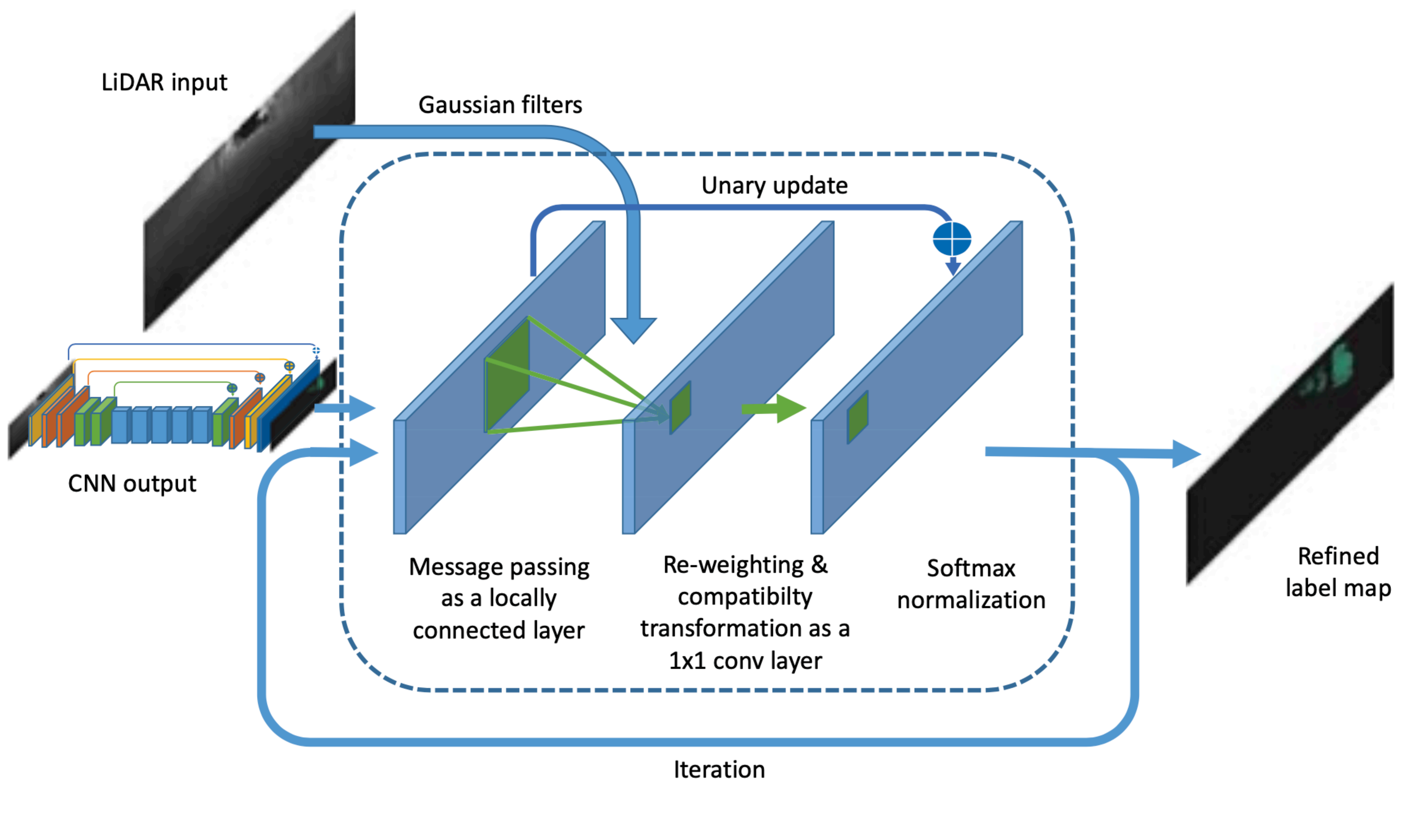
$$E(\mathbf{c}) = \sum_i u_i(c_i) + \sum_{i,j} b_{i,j}(c_i, c_j).$$

$$u_i(c_i) \;=\; -\log P(c_i)$$

$$b_{i,j}(c_i, c_j) = \mu(c_i, c_j) \sum_{m=1}^{M} w_m k^m(\mathbf{f_i}, \mathbf{f_j})$$

$$\mu(c_i, c_j) \;=\; 1 \text{ if } c_i \neq c_j \text{ and } 0 \text{ otherwise.}$$

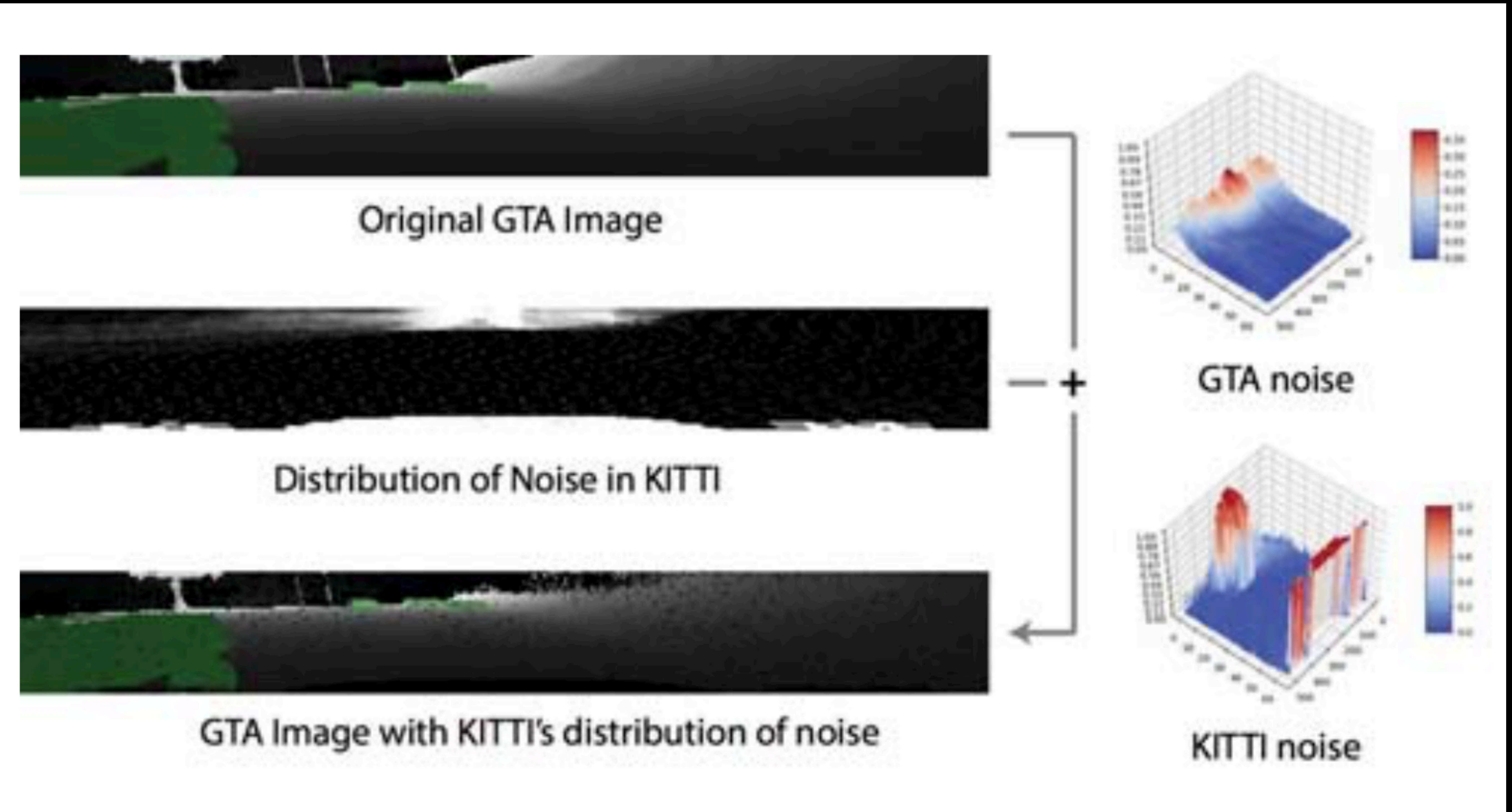
Conditional Random Field (CRF) as an RNN layer.



METHOD DESCRIPTION

Data collection

- KITTI raw dataset
- Synthesized dataset from GTAV
  - Add noise by KITTI’s distribution of noise



Experimental Result

TABLE I: Segmentation Performance of SqueezeSeg

		Class-level			Instance-level		
		P	R	**IoU**	P	R	**IoU**
car	w/ CRF	66.7	95.4	64.6	63.4	90.7	59.5
	w/o CRF	62.7	95.5	60.9	60.0	91.3	56.7
pedestrian	w/ CRF	45.2	29.7	21.8	43.5	28.6	20.8
	w/o CRF	52.9	28.6	22.8	50.8	27.5	21.7
cyclist	w/ CRF	35.7	45.8	25.1	30.4	39.0	20.6
	w/o CRF	35.2	51.1	26.4	30.1	43.7	21.7

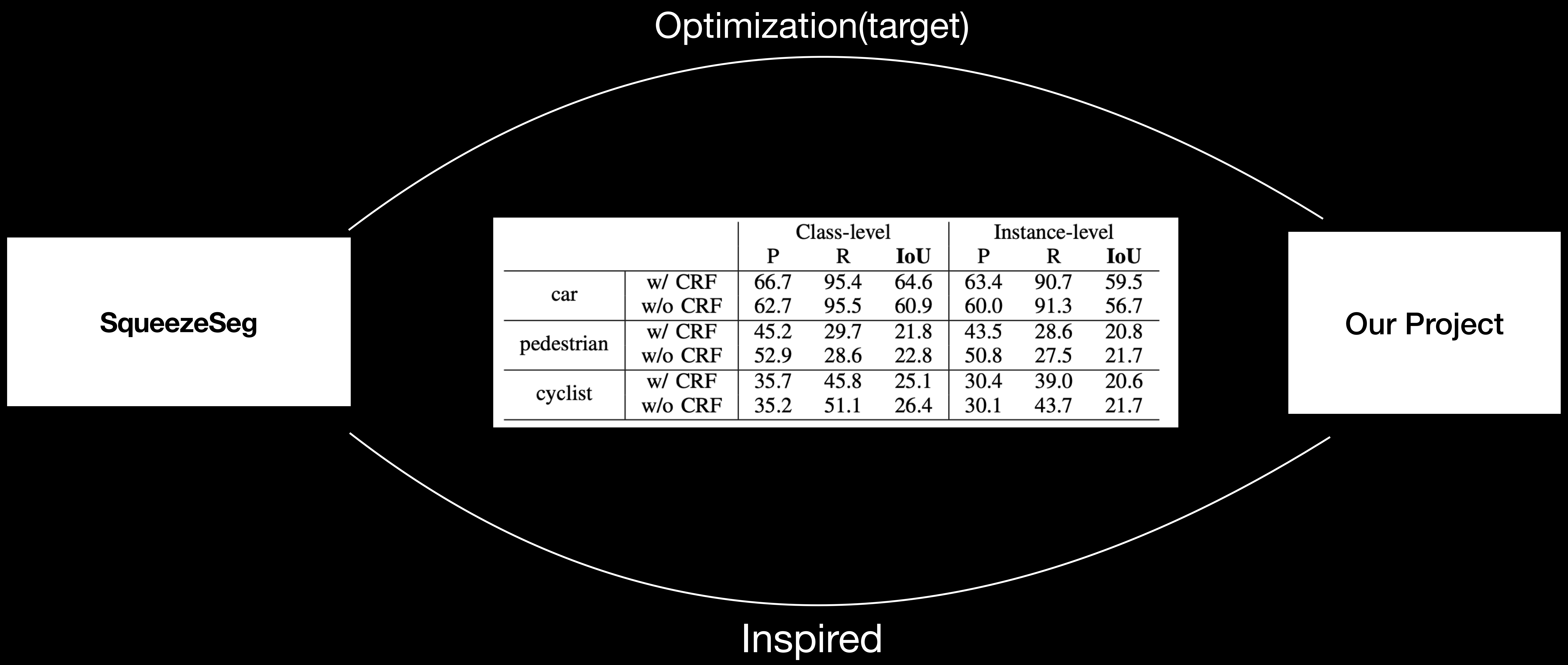
TABLE II: Average runtime and standard deviation of the SqueezeSeg Pipeline

unit: ms	Titan X	Drive PX2 AutoCruise	Drive PX2 AutoChauffeur	Xeon E5 CPU
SqueezeSeg	13.6/0.8	74.0/0.8	37.8/1.7	-
SqueezeSeg w/o CRF	8.7/0.5	52.0/1.3	25.1/0.8	-
DBSCAN	-	-	-	27.3/45.8

TABLE III: Segmentation Performance on the Car Category with Simulated Data

	Class-level			Instance-level		
	P	R	**IoU**	P	R	**IoU**
KITTI	58.9	95.0	57.1	56.1	90.5	53.0
GTA	30.4	86.6	29.0	29.7	84.6	28.2
KITTI + GTA	69.6	92.8	66.0	66.6	88.8	61.4

how this paper is relevant to our project



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	w/o CRF	35.2	51.1	26.4	30.1	43.7	21.7