Vehicle Trajectory Prediction in Crowded Highway Scenarios Using Bird Eye View Representations and CNNs

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Universidad de Alcalá

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Outline

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Motivation

Vehicle Trajectory Prediction Problem

- Structured or unstructured scenarios
- Multi-agent problem
- What variables should be used?
- How can it be modeled?
  - Kinematic or dinamic models
  - Rigid interaction-aware models

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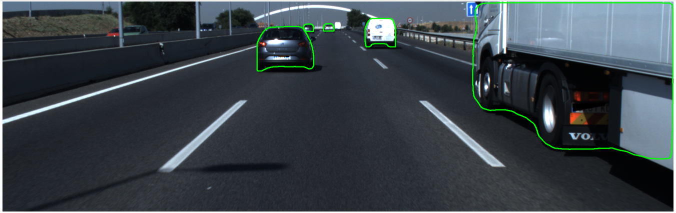

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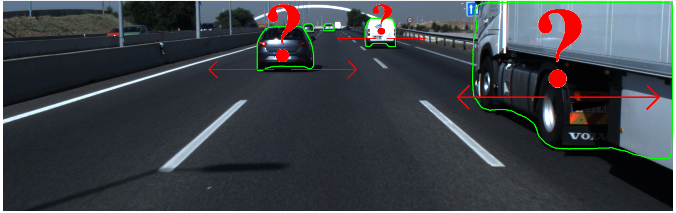

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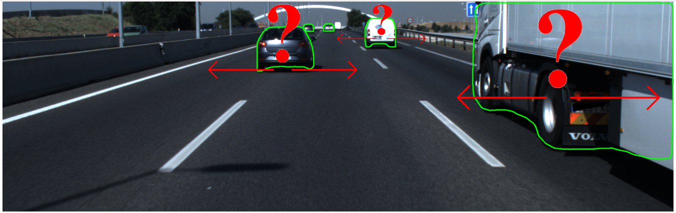

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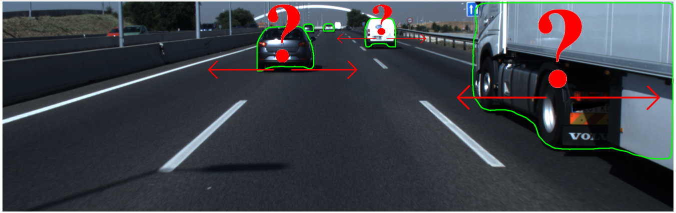

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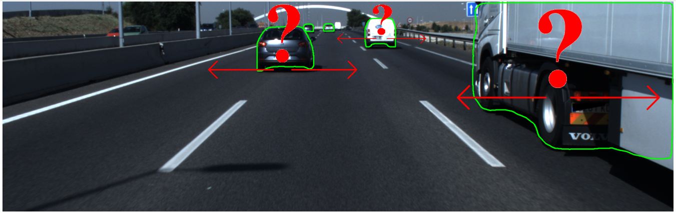

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Our proposal

A deep learning-based trajectory prediction approach based on graphic representations

- Motion and interaction histories
- Allows context integration
- Unlimited in number of vehicles
- No vehicle-centered
- Simultaneous prediction
- Unlimited but fixed range and prediction horizon

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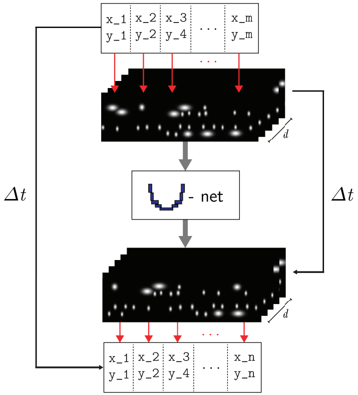

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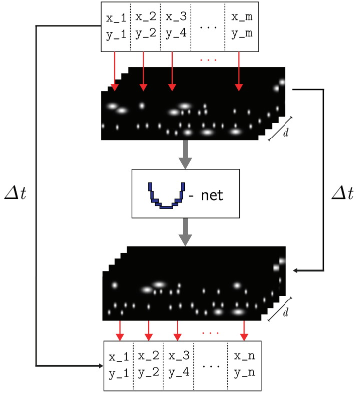

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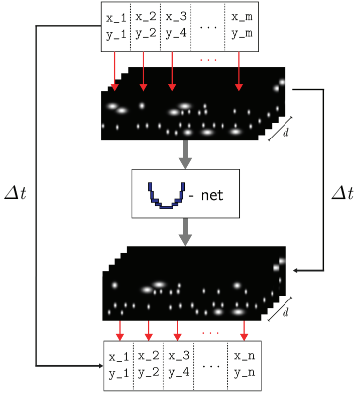

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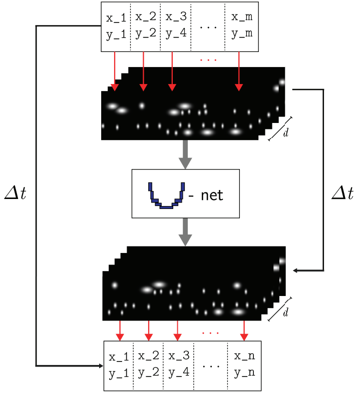

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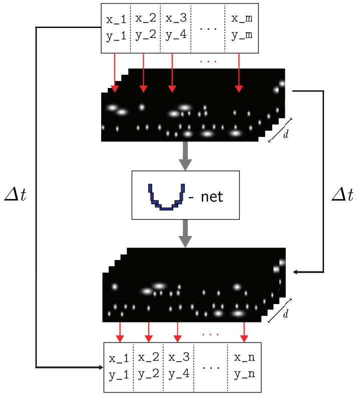

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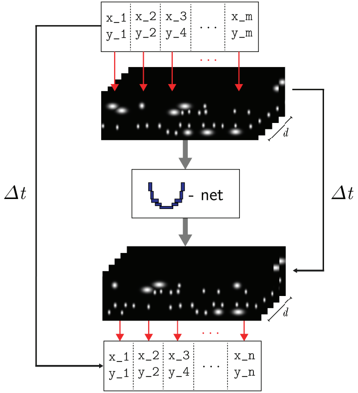

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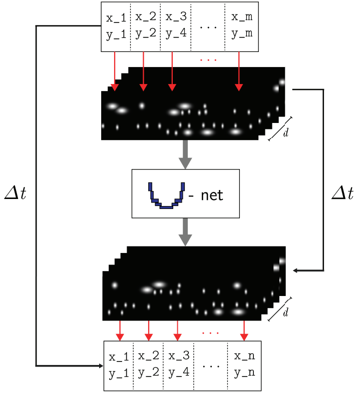

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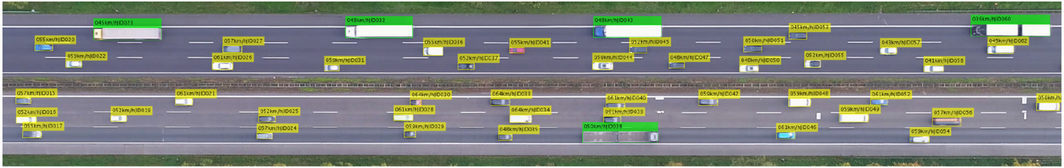
HighD Dataset[1]

- Publicy available at highd-dataset.com
- Road Structure
- Unique IDs
- Vehicle dimension
- Position, Speed, and Acceleration at 25 Hz

	HighD	Challenge
Samples	39M	1500K
Vehicles	110K	110K
Hours	147	16
Clips	60	60



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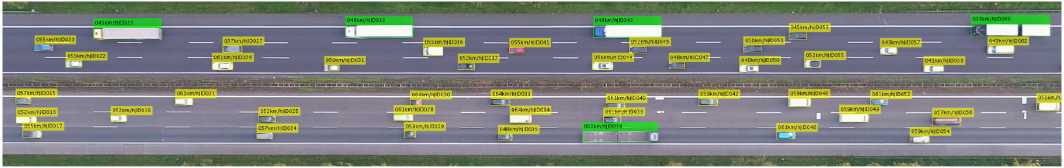

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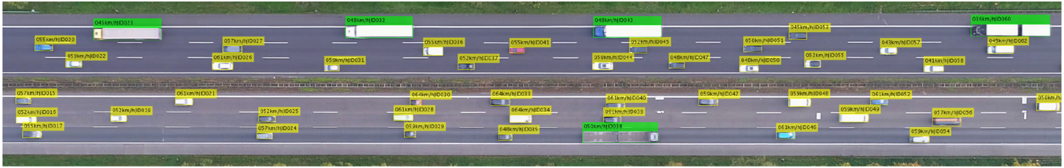

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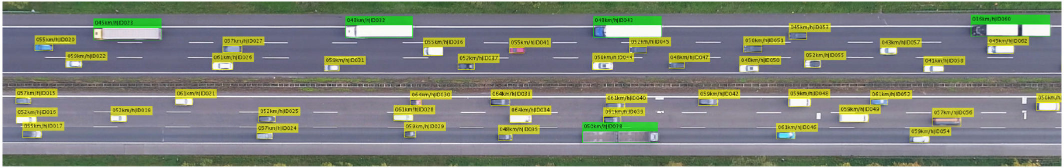

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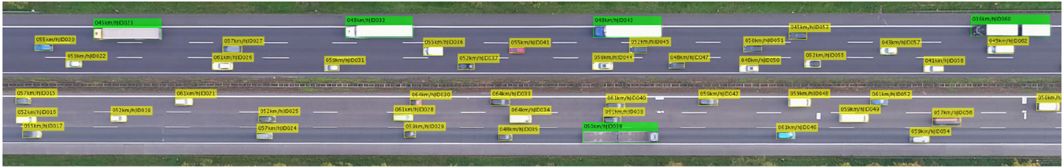

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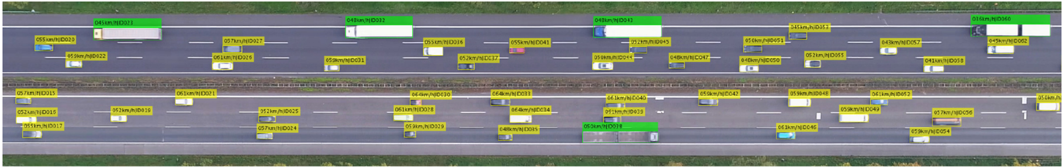

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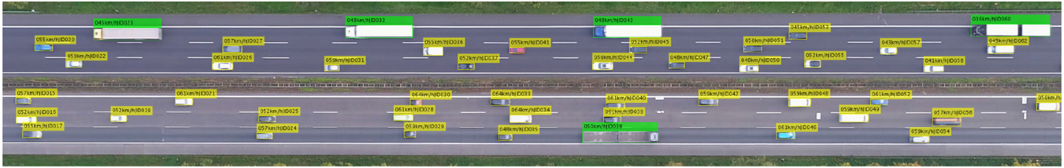

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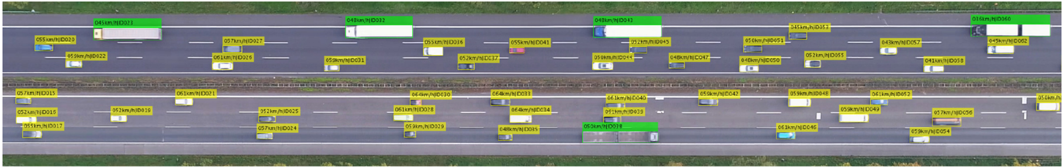

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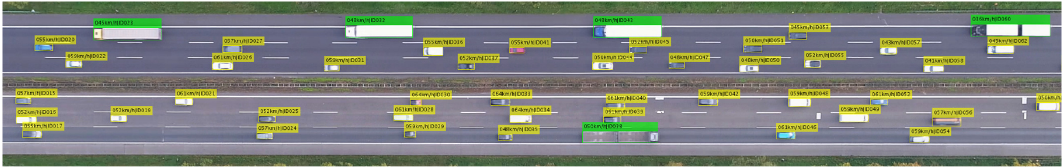

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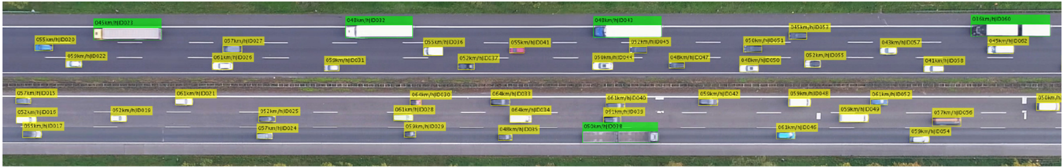

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Data Codification

- Driving Area as an Image: 32x512 m. $\rightarrow$ 64x512 px.
- Vehicles as $\mathcal{N}(\mu, \sigma^2)$
- Possible Overlap $P(x, y) = \max\{\mathcal{N}_i\} \quad \forall i$
- Only Predictable Vehicles

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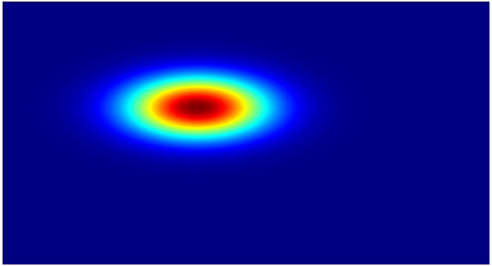

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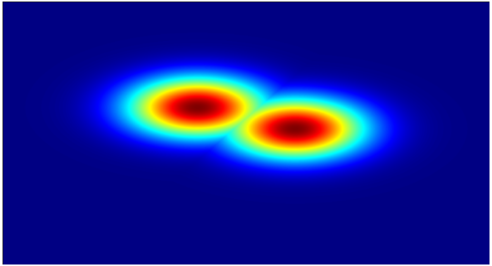

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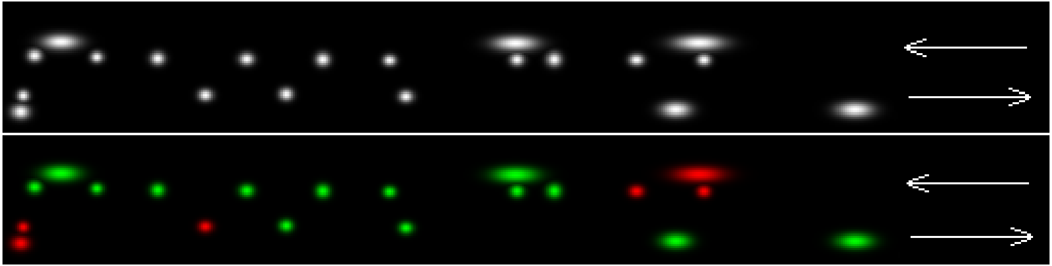

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  - Search the pixel with the higest probability
  - Compute the mass center
  - Reset the area
- Vehicle association by Euclidean distance

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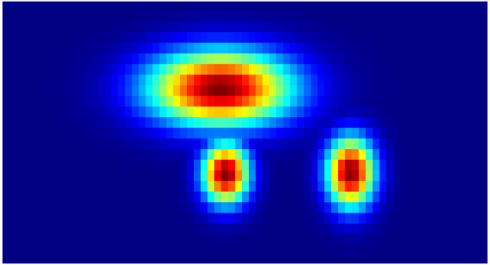

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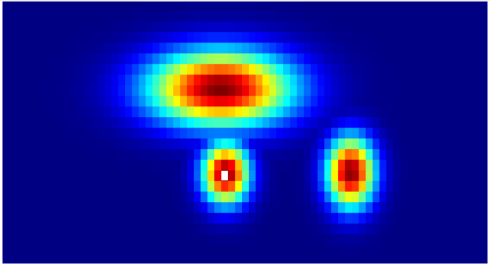

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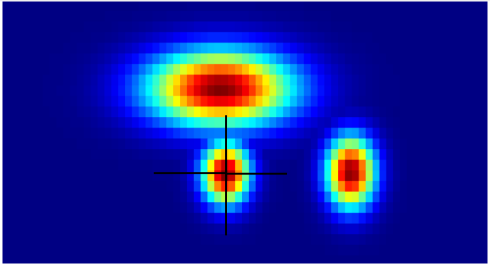

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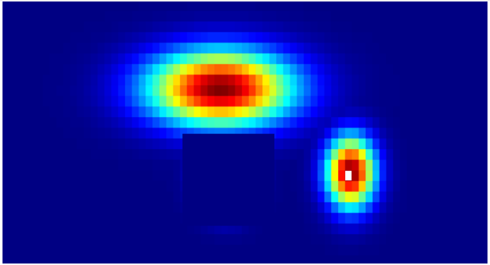

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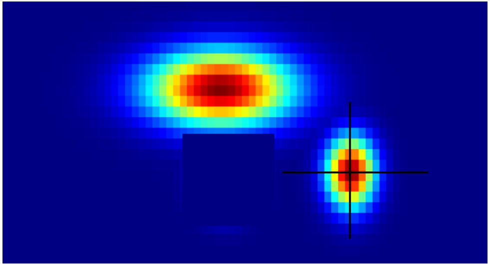

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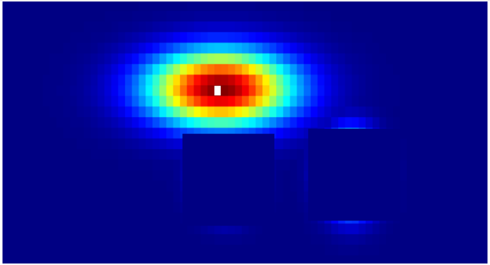

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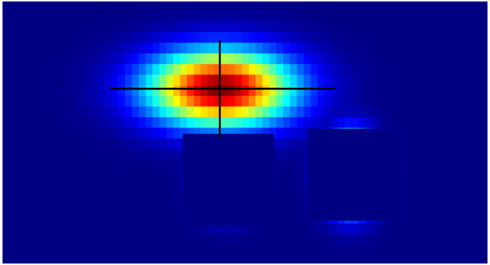

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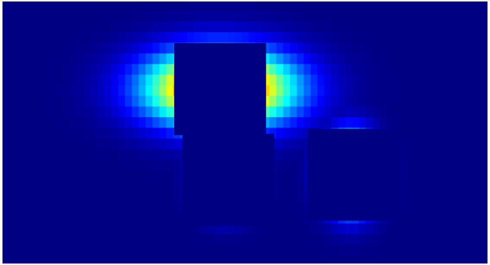

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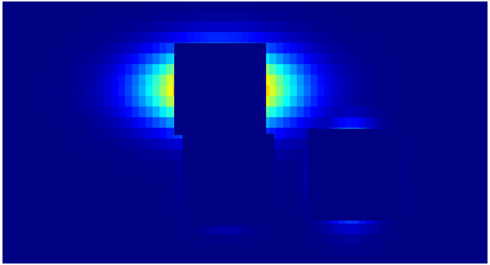

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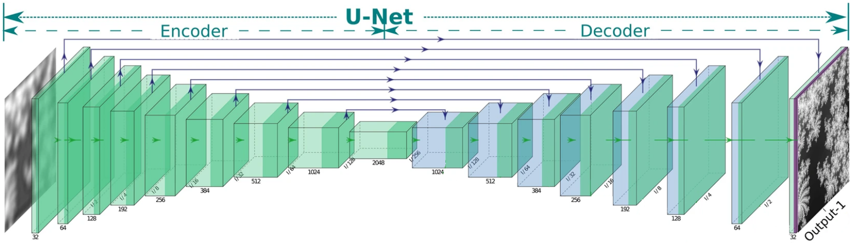
U-net model

- Number of filters.
- Depth levels.

Depth levels	4	5	6	7
Receptive Field	± 76	± 156	± 316	± 636
Input size	16	32	64	128
Parameters	56k	116k	235k	472k



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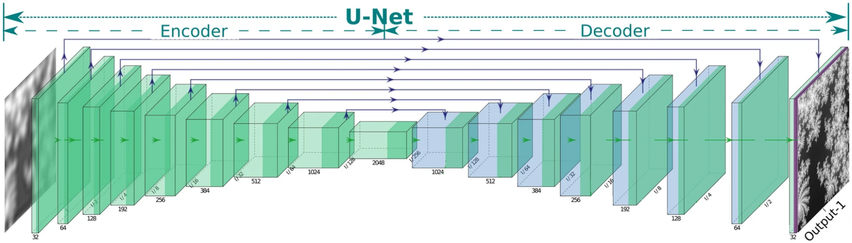

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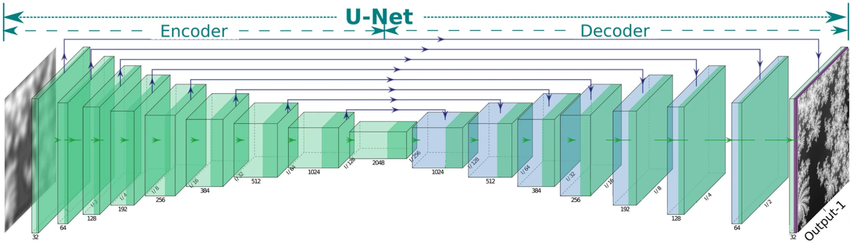

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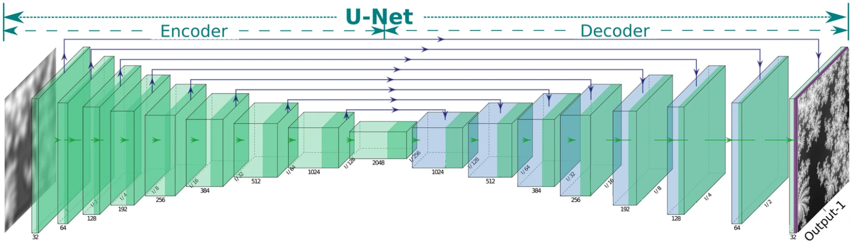

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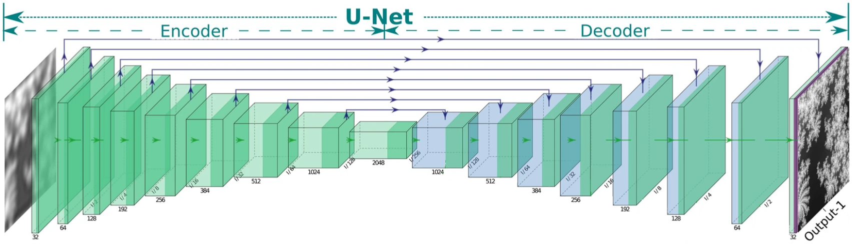

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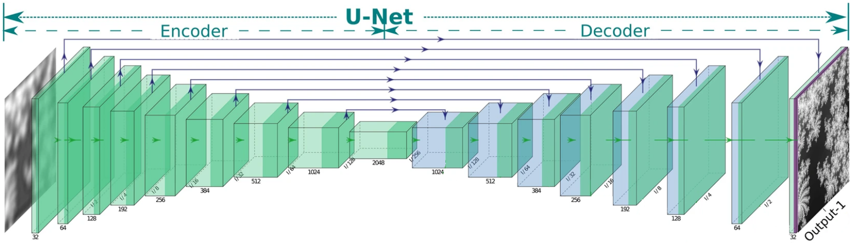
Depth levels	4	5	6	7
Receptive Field	± 76	± 156	± 316	± 636
Input size	16	32	64	128
Parameters	56k	116k	235k	472k



U-net model

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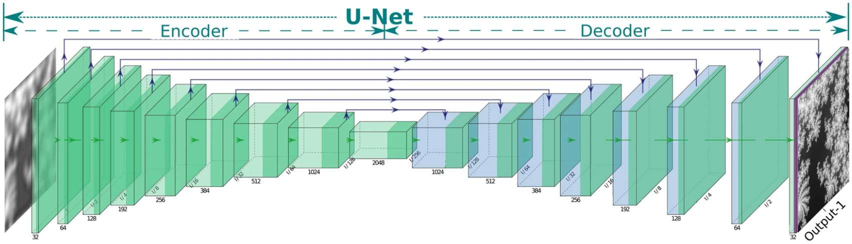

Problem Application

- Data rate lowered to 5 Hz
- Input & Output
  - 15@64x512 BEV
  - $-2.8 \leq t \leq 3.0$
- Activation Layer:
  - Linear
  - Clipped Rect. Linear Unit
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Network Architecture

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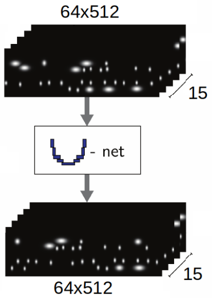

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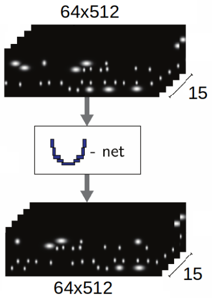

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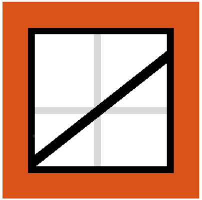

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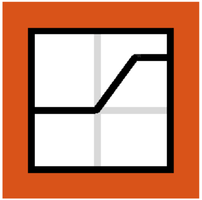

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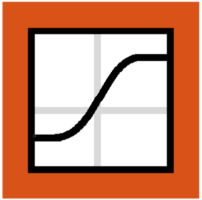

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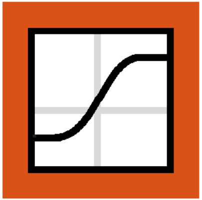

Outline

Results

Training setup

- Seq 1-20 28K samples
- Mini-batch size 1
- Epoch 1
- Learning rate 10^{-6}
- Momentum 0.9
- Loss function SE

Test Results

- Seq 21-25 7K samples
- Position MAE

	$t = 0.2$	$t = 3.0$
Model	ε_x / ε_y	ε_x / ε_y
Const. acc.	0.02 / 0.00	0.23 / 0.17
d = 5, f = linear	0.52 / 0.17	2.36 / 0.54
d = 6, f = linear	0.23 / 0.01	1.23 / 0.07
d = 5, f = tanh	- / -	- / -
d = 6, f = tanh	- / -	- / -
d = 5, f = cRelu	0.74 / 0.38	2.51 / 0.94
d = 6, f = cRelu	0.46 / 0.22	2.06 / 0.62

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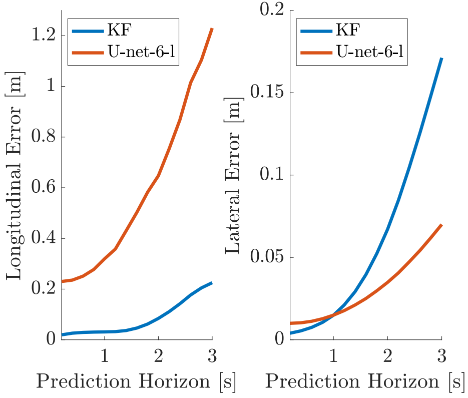


Results

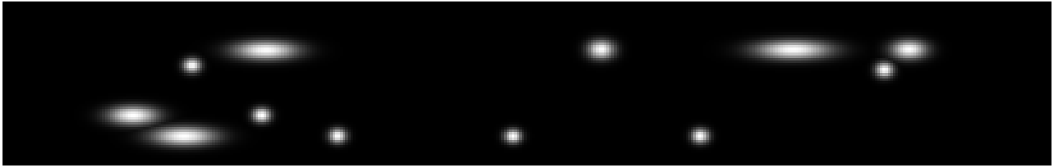
Results Example

Input block example

Output block example ($\times$ = *GT* $+$ = *Pred*)

Results Example

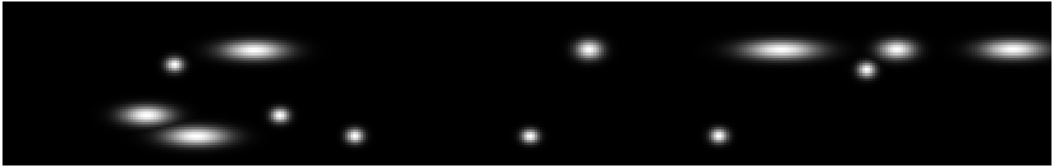
- Input block example
- Output block example (× = *GT* + = *Pred*)



Results Example

Input block example

Output block example (× = GT + = Pred)



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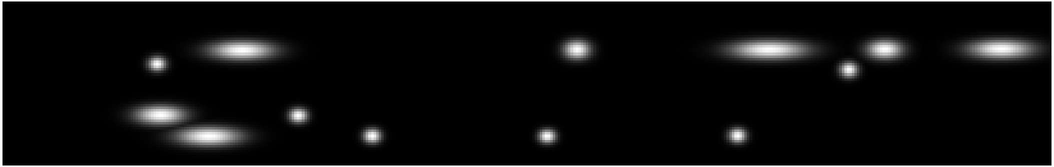

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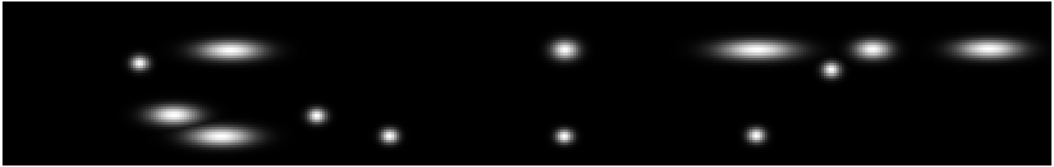

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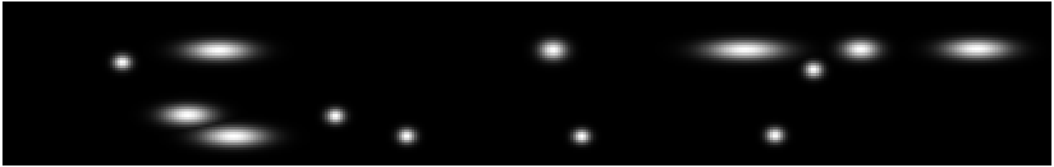

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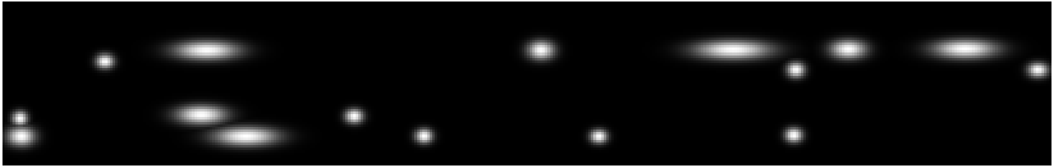

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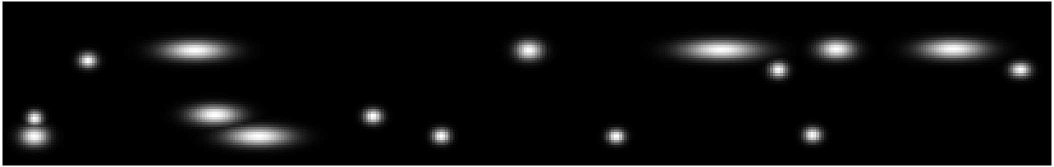

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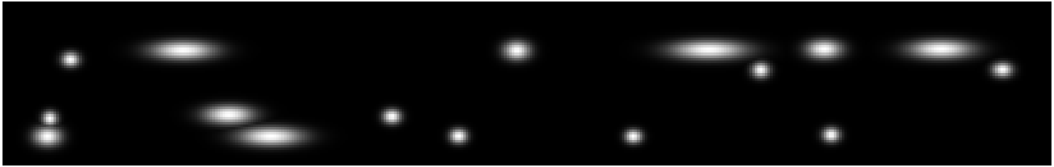

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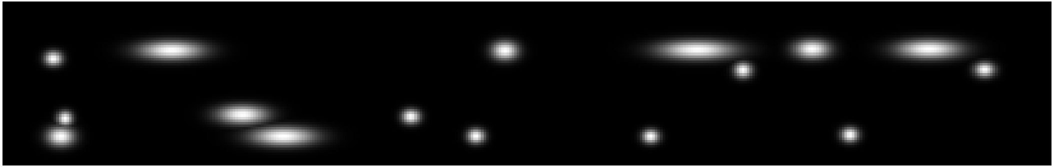

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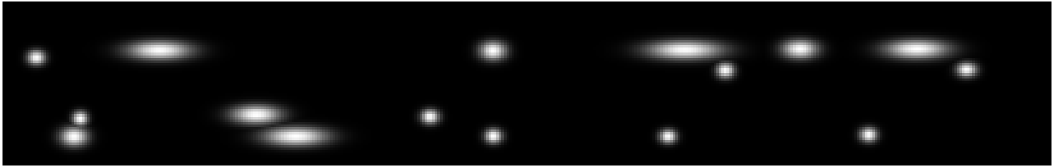

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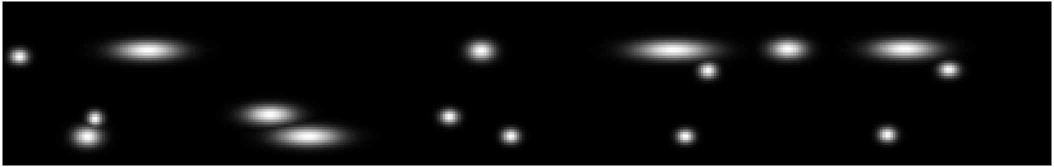

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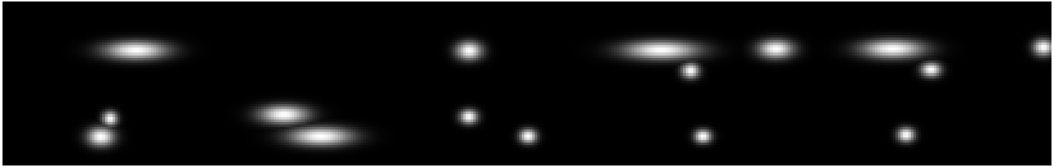

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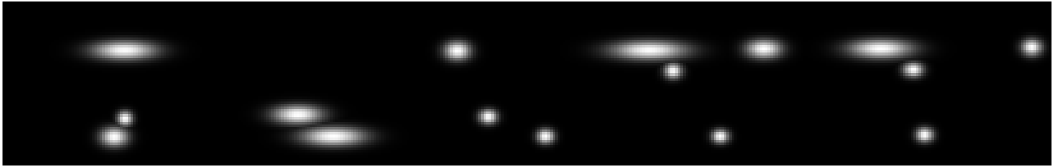

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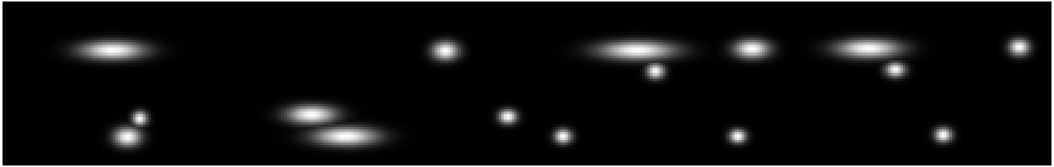

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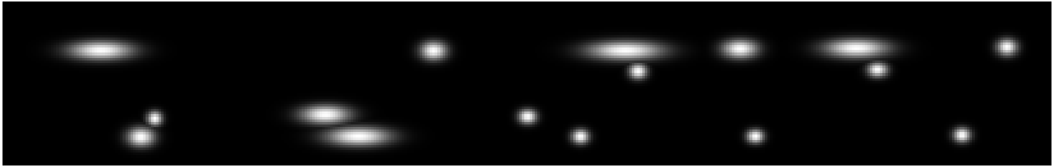

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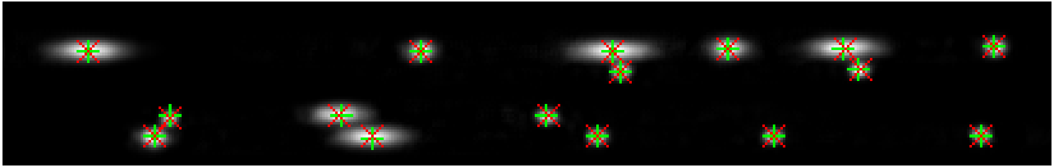

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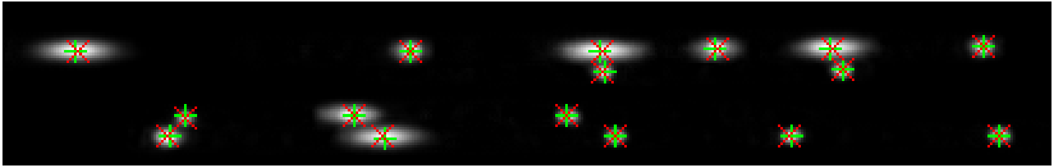

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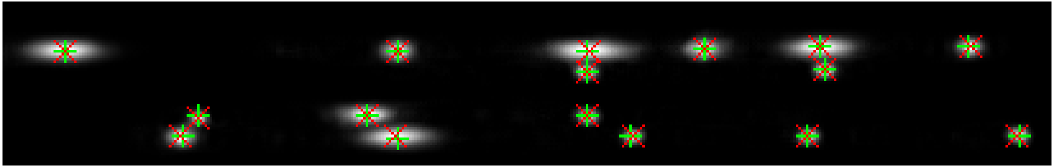

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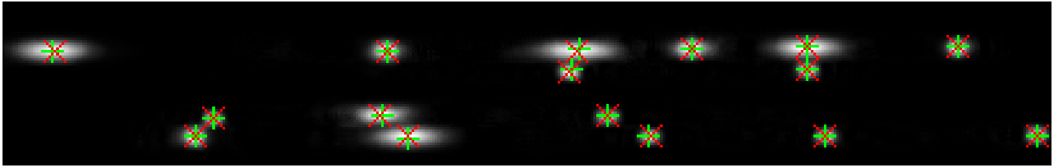

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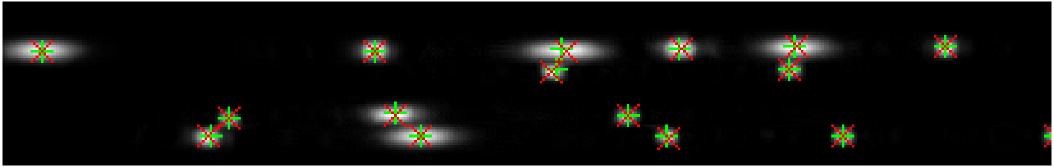

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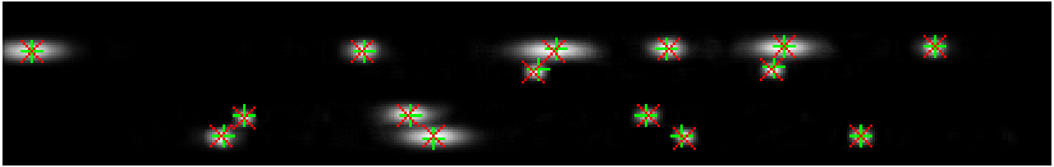

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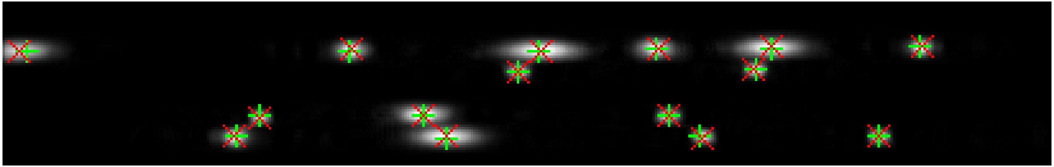

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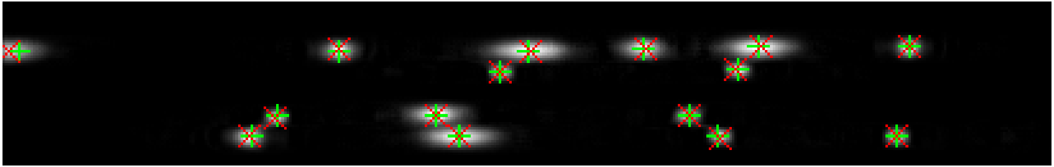

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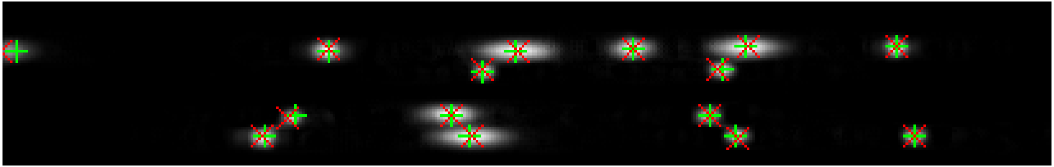

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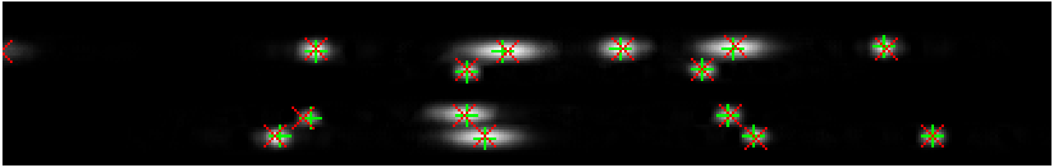

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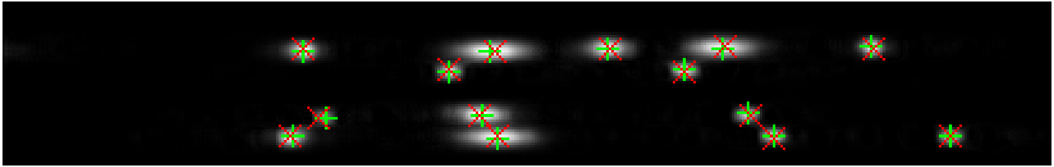

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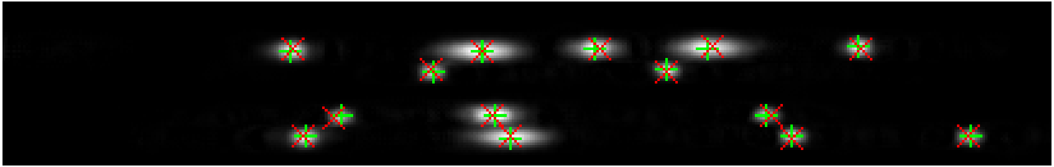

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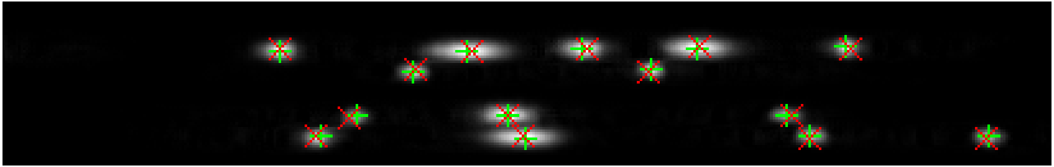

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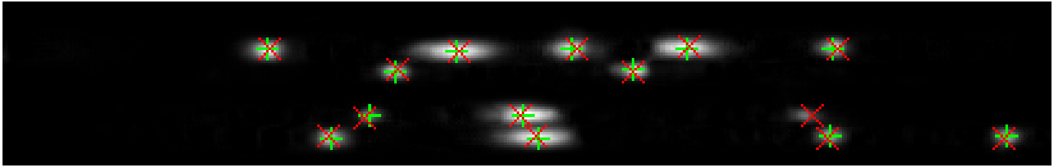
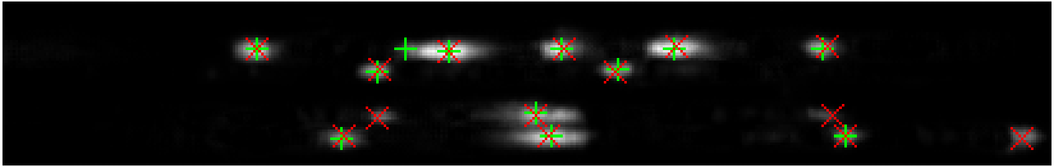


Results Example

Input block example

Output block example ($\times$ = *GT* $+$ = *Pred*)



Outline

Conclusions & Future Work

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- The U-net model has been adapted to predict trajectories
- Prediction are performed simultaneously in an interactive way
- U-net overcomes const. acc. model in lateral prediction

Future Work

- Improve the vehicle extraction method
- Modify parameters to train deeper U-net configurations
- Apply this approach to intersection and roundabout scenarios

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20th September 2020