Ghost Target Detection in 3D Radar Data using Point Cloud based Deep Neural Network

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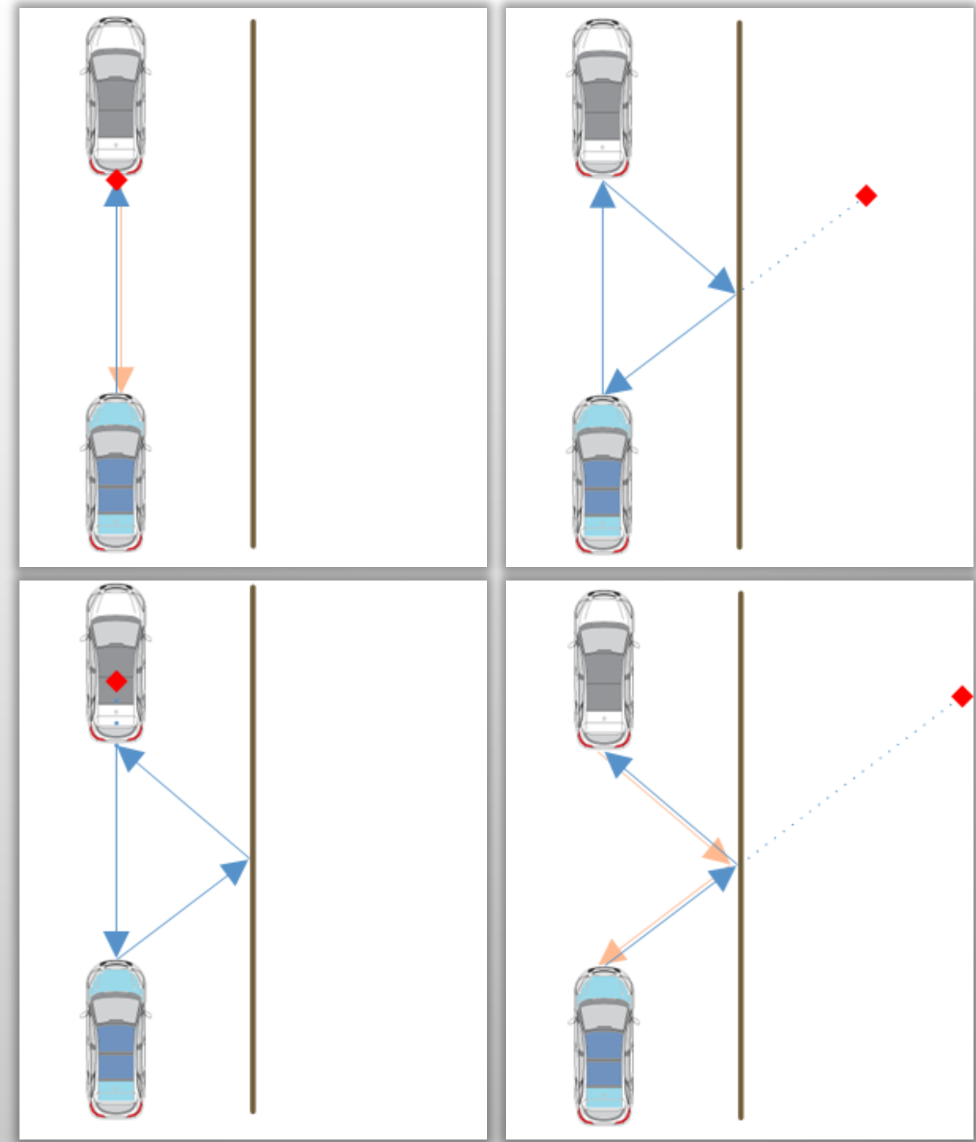
Introduction

Why Radar?
- Cost effective
- Robust to weather conditions
- Simultaneous velocity and position measurement

What is a Real/Ghost Radar Target?
- A **real** radar measurement is caused by **direct** incident and reflected radio waves.
- A **ghost** radar measurement is caused by multi-path radio waves.
- A multi-path wave is caused by either an **indirect** incident or reflected wave, or both.



Existing Work

Model based approaches

- Roos et al. [1] compare measured velocity vector orientation to the orientation of the vehicle model and a mismatch between the orientations indicates a ghost target

Models can be inaccurate, and not representable of real driving scenarios

Data driven approaches

- Ryu et al. [2] use a fixed traffic control radar and hand-crafted features to train a multilayer perceptron
- Prophet et al. [3] compare random forest classifiers to support vector machines and k-nn algorithms
- Garcia et al. [4] use an encoder-decoder deep CNN to detect ghost targets in low resolution 2D radar data

*Current approaches can't deal with **high resolution** and **3D radar point clouds***

Dataset used

- Measured by an Astyx 6455 HiRes radar sensor, a sample of which is provided by Meyer et al. [5]

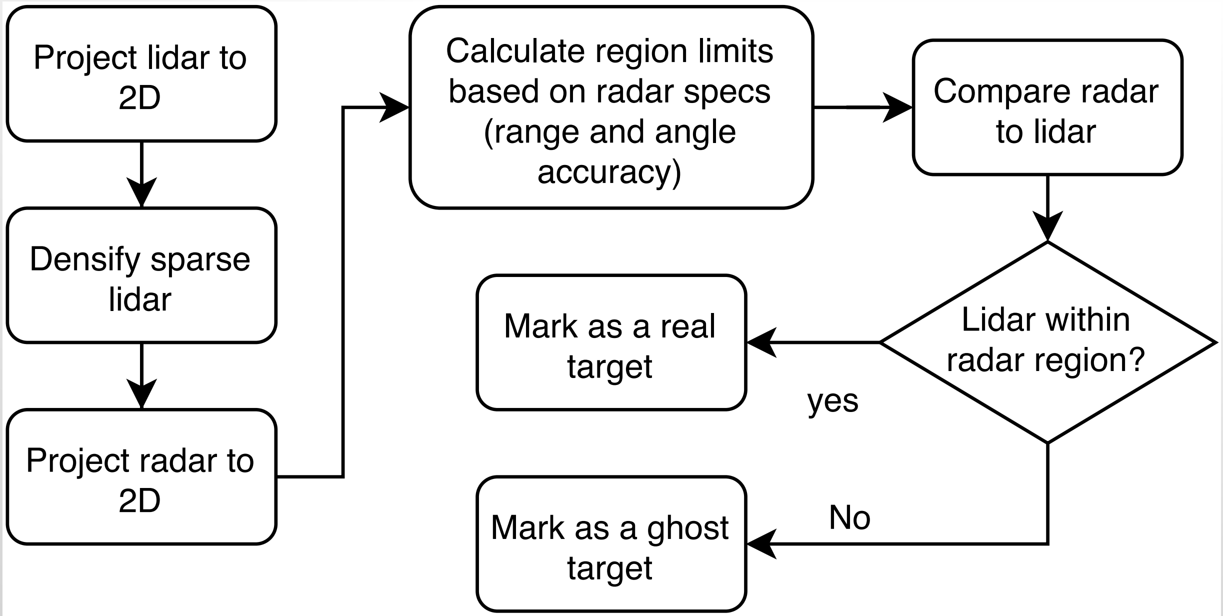
Ground Truth Generation

Why?

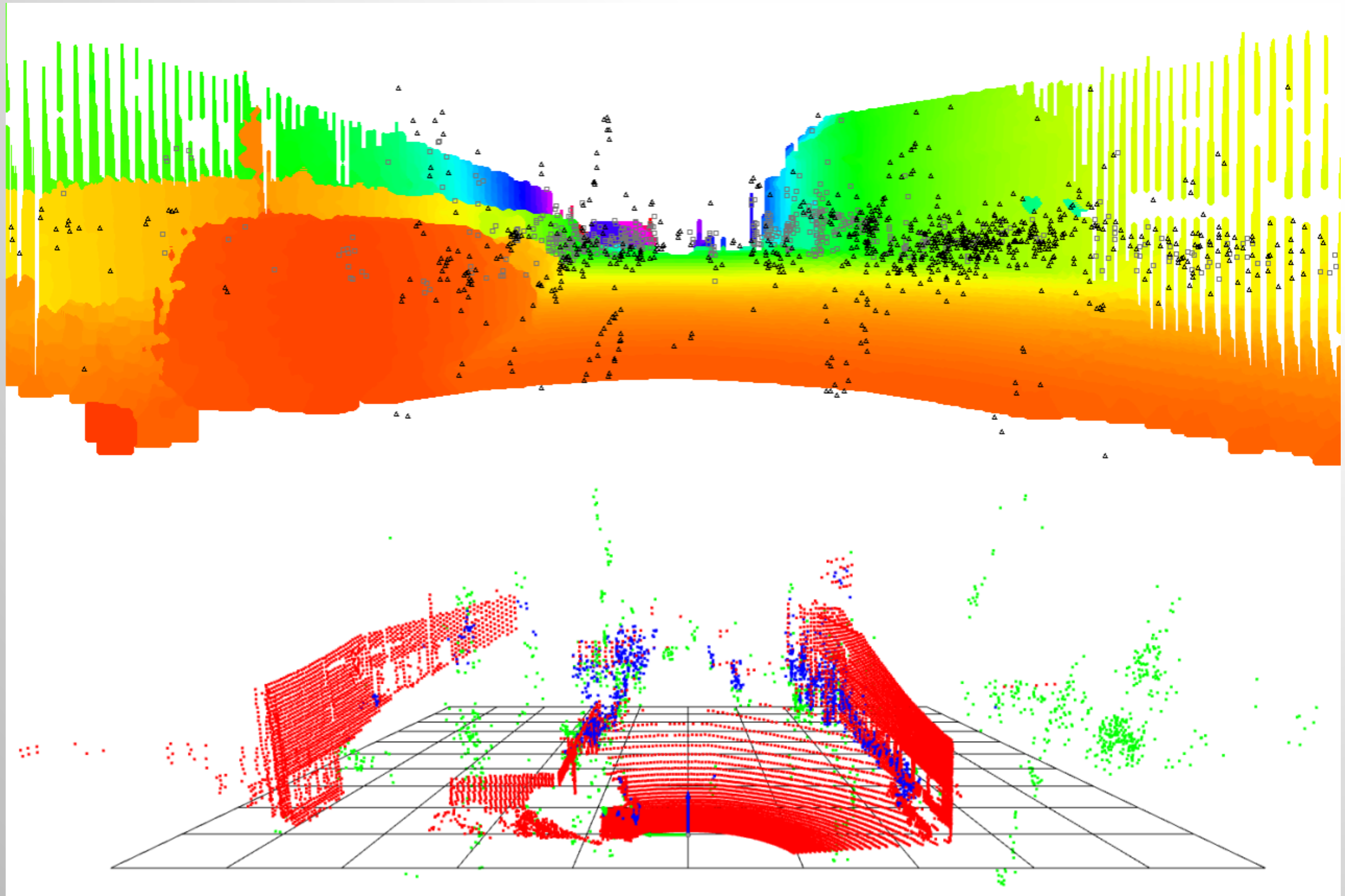
- Free datasets with ghost target annotations are currently not available
- Manually labelling frames is very time consuming and error prone

How?

- Lidar data is projected to 2D and densified using the method by Ku et al. [6]
- Radar data projected to 2D for depth comparison
- Polygon regions are calculated in 2D based on radar tolerances
- Radar data with corresponding lidar depth in polygon region are considered real, otherwise ghost



Ground Truth Generation

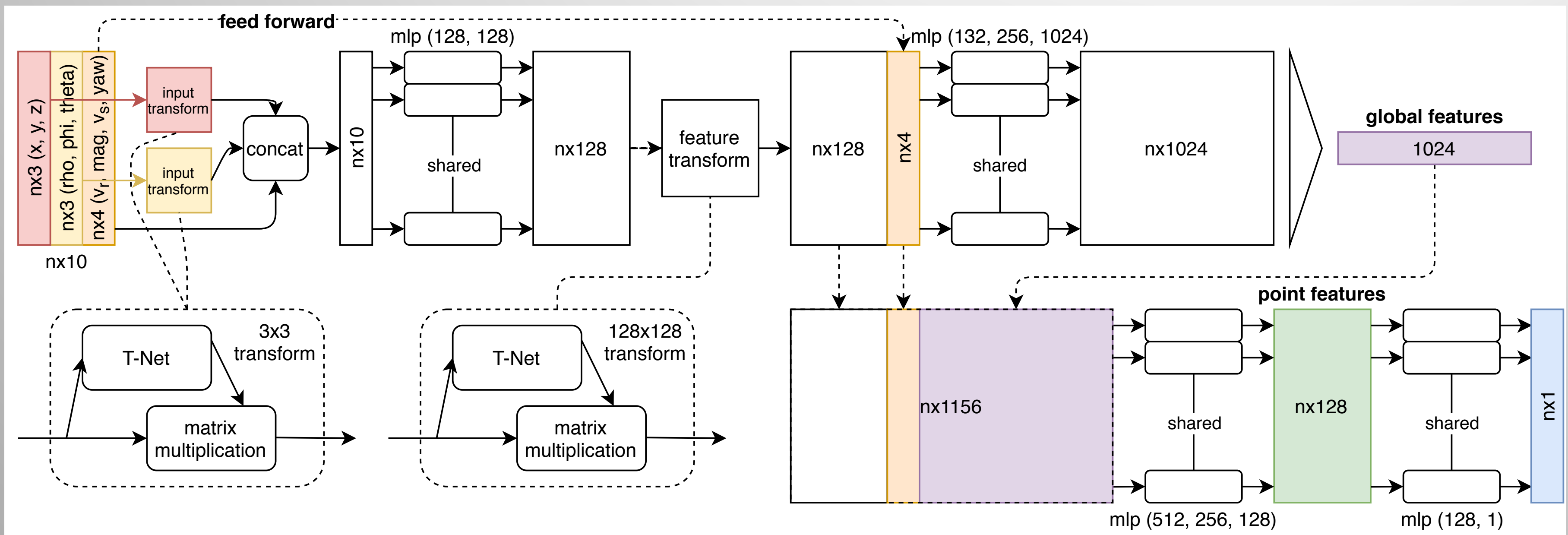


- The dense depth map calculated based on the lidar data with an overlay of a sample of radar points. The light-colored squares correspond to **real** points based on their depth value, conversely the dark-colored triangles correspond to **ghost** points
- The 3D perspective showing the **real** points in blue, coinciding with surfaces detected by the lidar. The **ghost** points are in green and can be seen behind lidar surfaces or missing a reference lidar measurement

Network Architecture

- Based on the PointNet [7] architecture
- Modifications to accommodate the data
- Class-balanced loss to counteract imbalances in data
- Cross validation for evaluation

- Expanded input includes:
  - Spherical coordinates
  - Vehicle velocity and orientation
- Separate input transforms for cartesian and spherical coordinates
- Feed forward of the non-coordinate inputs to a later stage for higher output influence



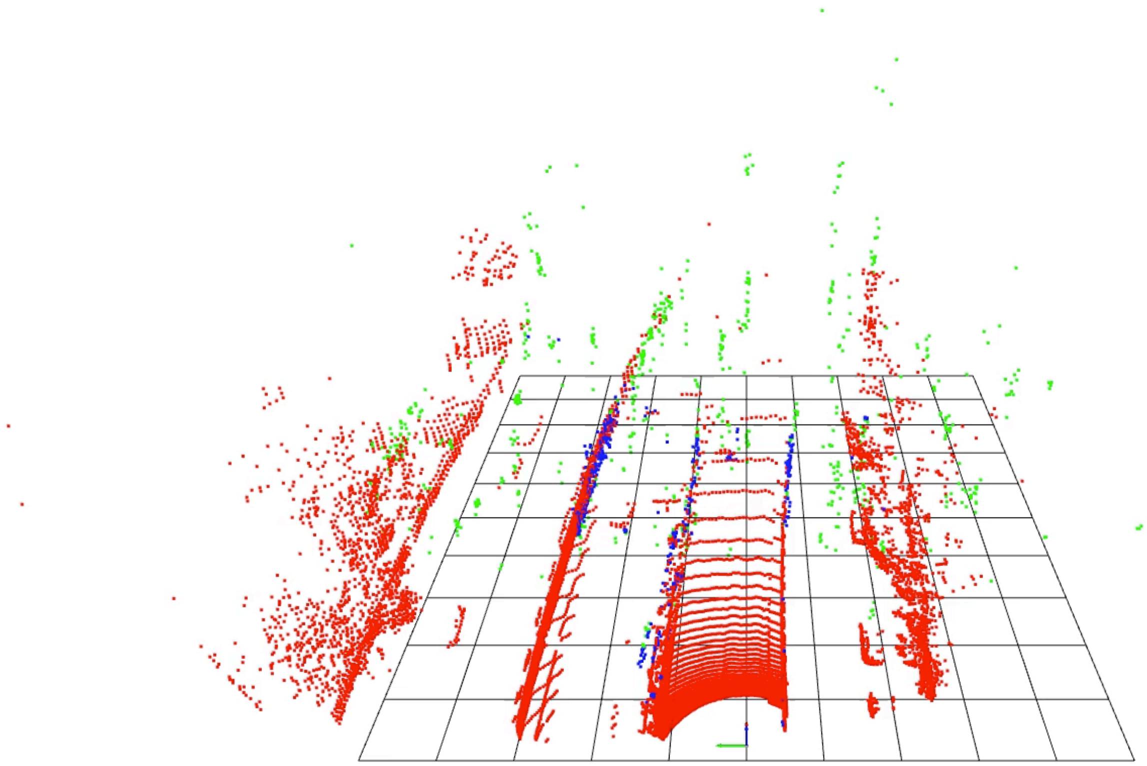
Evaluation and Results

- The changes introduced to the network significantly improved the results
- The combination of adding spherical coordinate inputs and vehicle state information caused the biggest improvement
- A small additional improvement was seen when adding a skip connection for tighter input-output correlation

Network	mIoU	IoU Ghost	IoU Real	F1 Ghost
Baseline	61,41%	55,91%	66,90%	71,72%
10 input features	65,13%	58,53%	71,73%	73,84%
10 feats & skip connection	**65,38%**	**58,63%**	**72,13%**	**73,92%**
7 feats & skip connection	64,52%	57,76%	71,29%	73,23%

- The baseline network is PointNet with input extended for velocity and reflection magnitude
- Setup with 10 input features. This network evaluates the importance of using **additional input features**
- Setup with 10 input and a skip connection. This is the network architecture presented and evaluates the usefulness of the **skip connection**
- Setup with 7 input and a skip connection. In this architecture we removed the **spherical coordinates** input to evaluate their importance

Qualitative Results



Conclusion

- Presented classification of real and ghost targets in 3D radar data
- Extended the PointNet architecture for the radar detection problem
- Presented an approach for automatic radar data labelling using lidar data
- Showed promising results in complex real measurement scenarios

Future Work

- Temporal information
- Deeper and more complex network architecture
- Improved ego vehicle information

Thank you for your attention!

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