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

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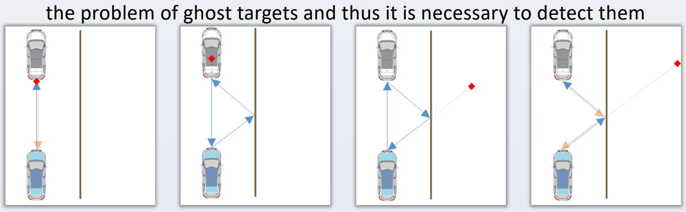
## Position

- The field of autonomous driving is of an ever-rising importance in the automotive industry
- Radar sensors have been an integral part of driver assistant systems but are now being tasked in adding more autonomy to vehicles
- To achieve higher levels of autonomy, robust detection and tracking of obstacles and other road users is necessary
- Due to the nature of their operation, radar sensors are susceptible to the problem of ghost targets and thus it is necessary to detect them



Real Target Ghost Targets

## Ghost Target Detection

**What are ghost targets:**

- 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

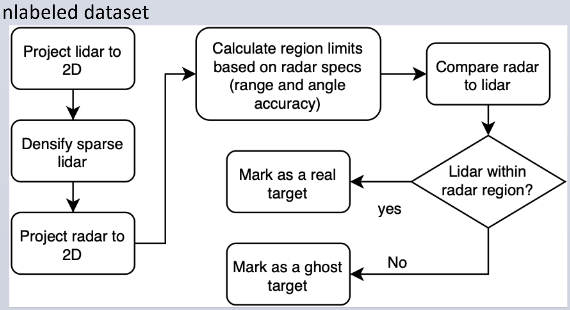
**Detection approaches:**

- **Model based:** 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:**
  - 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**

## Ground Truth Generation

- There are not many public datasets for automotive radar, and existing datasets do not label ghost targets
- Manually labeling thousands of frames for ghost targets is very time consuming and error prone due to the complexity of driving scenarios
  → We devise an approach to generate the required annotations to our unlabeled dataset

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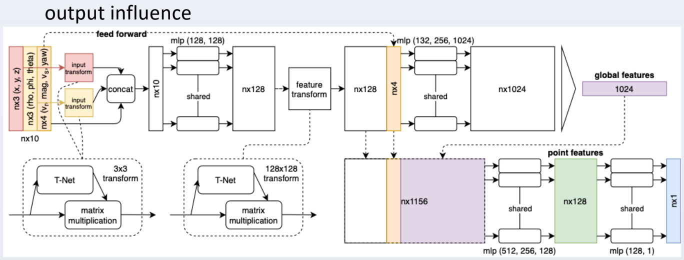
## Network Architecture

- Based on the PointNet [5] architecture with modifications to accommodate the data
- Uses class-balanced loss to counteract imbalances in data.
- 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




## Detection Evaluation

- Used class-balanced loss to counteract imbalances in data.
- Used cross validation for evaluation.

**Discussion:**

- 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 (PointNet: 5 in feats.) | 61,41% | 55,91% | 66,90% | 71,72% |
| 10 input features | 65,13% | 58,53% | 71,73% | 73,84% |
| 10 features & skip connection | **65,38%** | **58,63%** | **72,13%** | **73,92%** |
| 7 features & skip connection | 64,52% | 57,76% | 71,29% | 73,23% |

- 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 impact on the overall result

## References

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