Utilizing Super-Resolution for enhanced automotive Radar object detection

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APTIV

What’s this paper about ? 🤔

Camera can lead to poor perception quality. Can you trust a self-driving car with no radar at night?

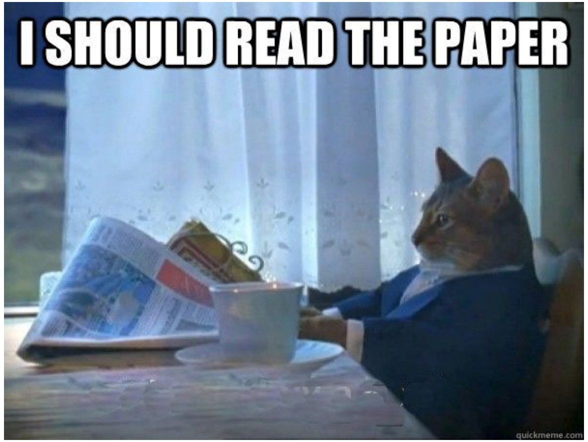
Can you count the number of people ?

Poor visibility in rain,fog, night,snow.

Image Credit : https://www.reddit.com/r/motorcycles/comments/16m8gyr/yall_watch_out_for_selfdriving_cars_out_therei/

https://x.com/docmilanfar/status/1706920735292498149?s=20

Why you should read this paper ? 🤷🏻‍♂️



- ➢ Radar-ML for autonomous driving systems.
- ➢ Radar is all you need. Avoid problems in sensor fusion.
- ➢ Easily deployable on low cost edge devices.
- ➢ A redundant separate independent radar-based object detection system.

The Giants Supporting Our Weight 💁🏻‍♂️

- ➢ Vision-based object detection
- ➢ Radar Super-Resolution
- ➢ Data generation through simulation

What did we do? 🧐

Two Contributions of the Paper

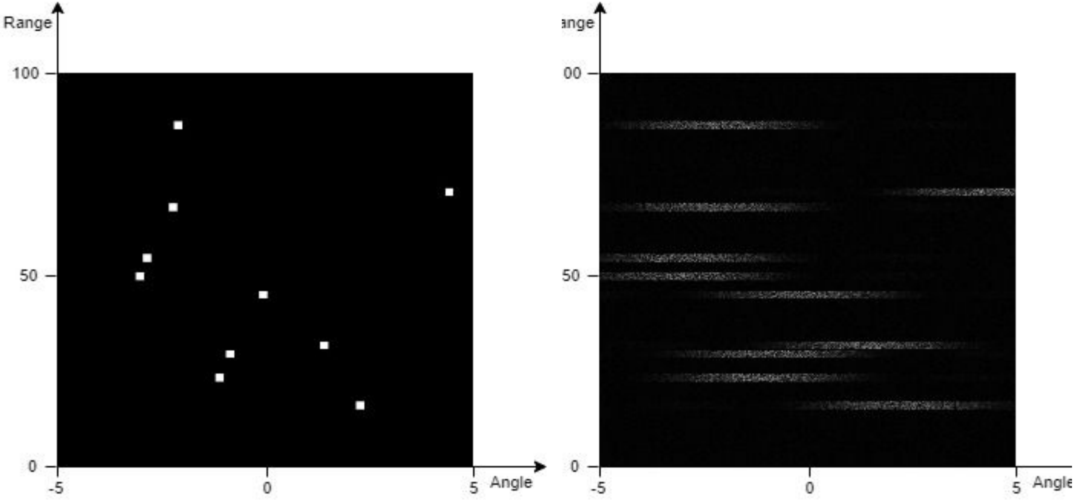
1

Three Dataset Generation
a) Simulated Radar data for LR-HR pair.
b) LR-HR pair of the CRUW dataset.
c) Segmented image patches from CRUW dataset (CRUW-Seg dataset)

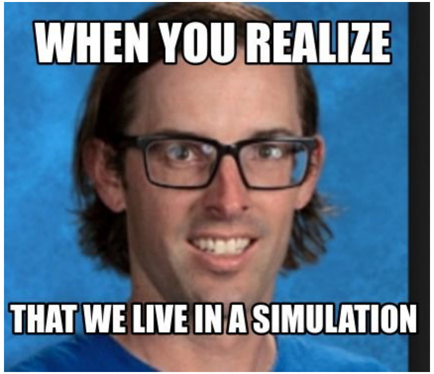
2

Object detection using **RADAR ONLY** super-resolution.

Simulate and Generate: Data in a Digital Disco! 🤖



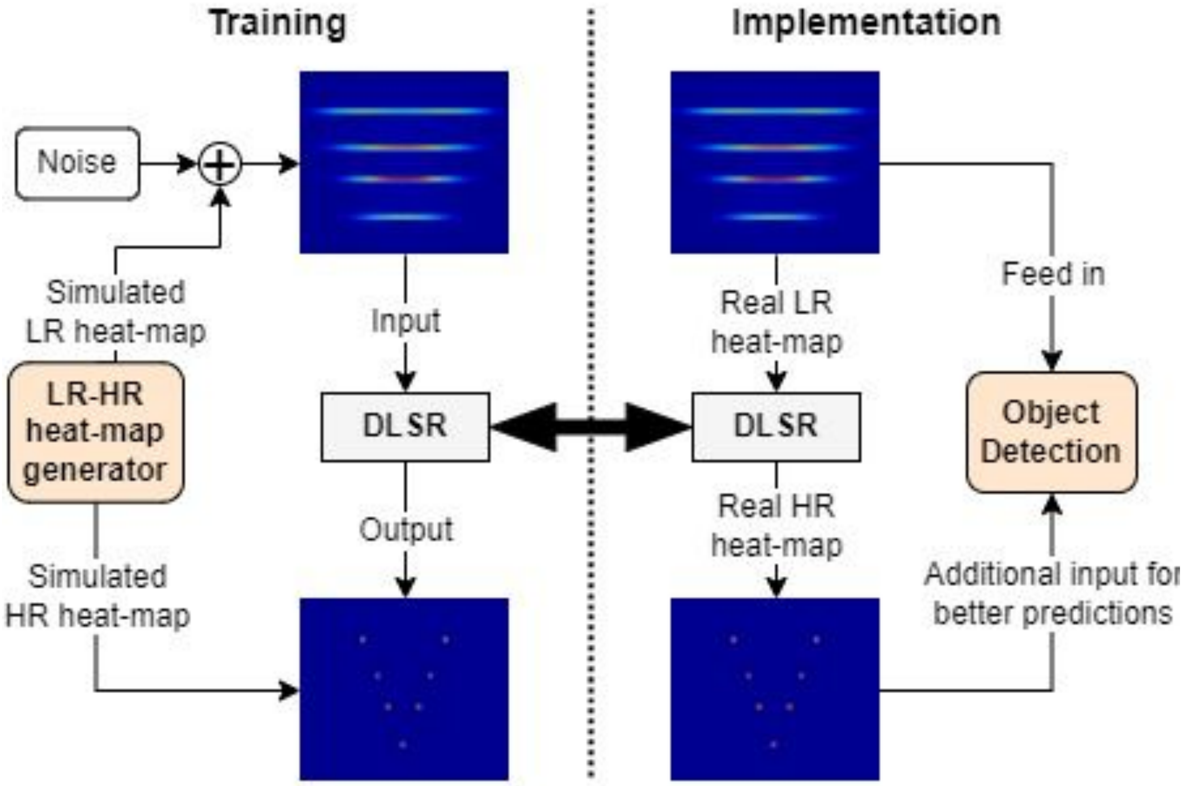
Polar radar images generated from the simulation.
Left - Ground truth (GT)/HR radar image
Right - LR radar image with added noise



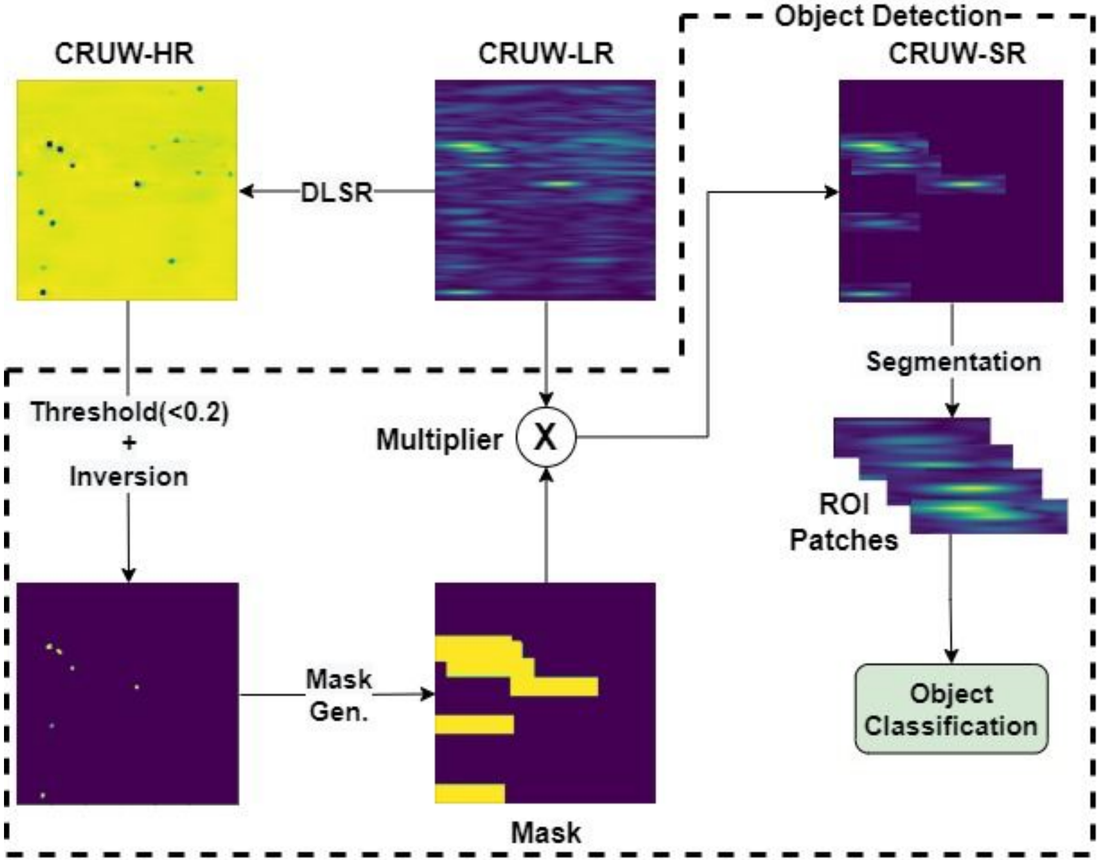
Simulation Parameters	Values
Range span	$[0, 100]$ m
Azimuth span	$[-5°, 5°]$
Range Resolution	0.097 m
Azimuth Resolution (LR,HR)	$3.5°$, $0.0097°$
Original Pixel Resolution	512×512
Original Object Shape(HR)	20×20
Smearing Function Used	Sinc Square
Main Lobe Width of Smearing Function	$3.5°$ (179 pixels)
Total Number of Side lobes taken	4
Number of objects (Sparse,Dense)	4,10

Values for the simulation parameters

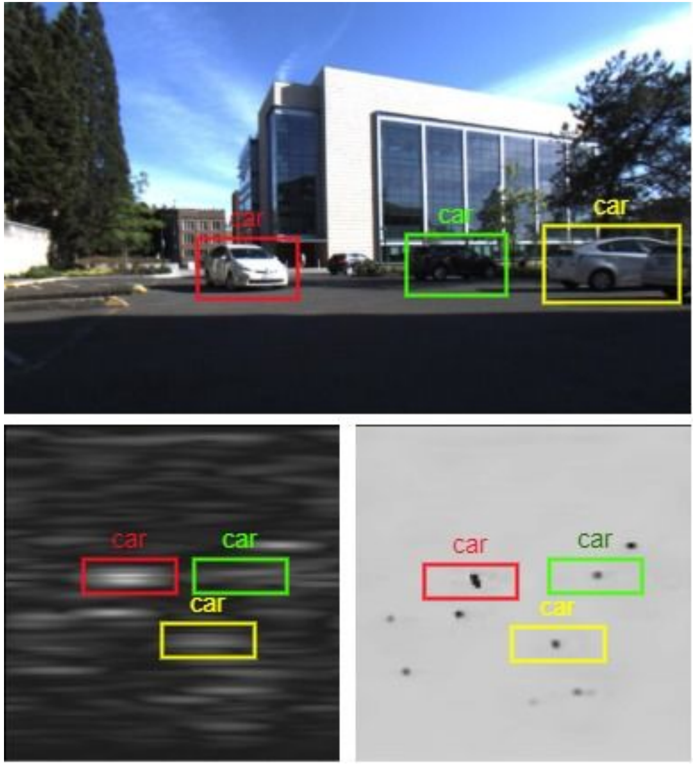
Master Plan 👨‍🏫

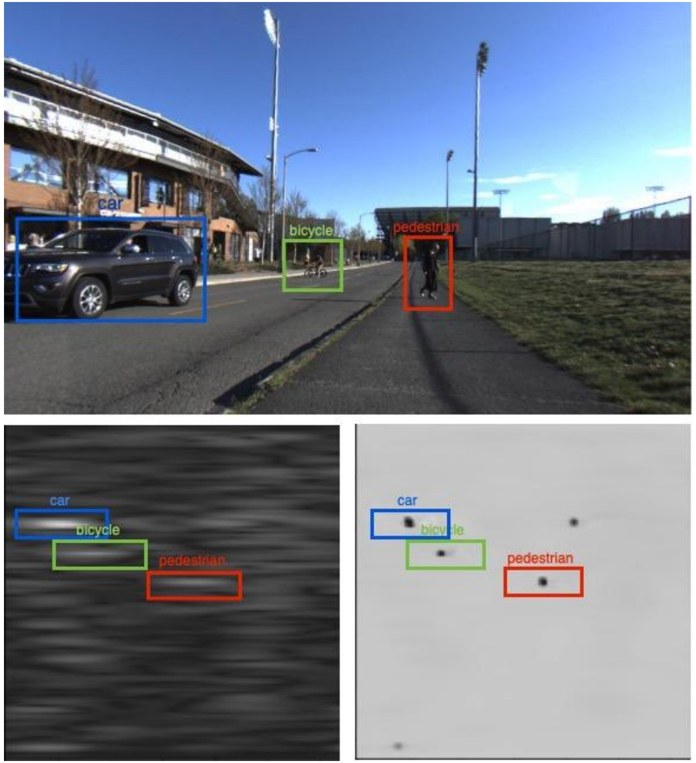

Training
Implementation
Noise
Simulated
LR heat-map
LR-HR
heat-map
generator
Simulated
HR heat-map
Input
DLSR
Output
Real LR
heat-map
DLSR
Real HR
heat-map
Feed in
Object
Detection
Additional input for
better predictions

Our Secret Ingredient



Results: Where science meets surprise endings ✅





Two examples : Top - Camera image of the corresponding scene, Left bottom - Original CRUW Low-resolution Image. Right bottom - Final CRUW high-resolution images as predicted by the Super-resolution model.

Tables: Images are just pixels in comparison! 🥲

Network	Val Acc(%)	Parameter Count
Ours(3-class)	80.0	14.7k
Ours(4-class)	75.0	14.8k
RaDICaL(linear)* [18]	83.1	1.7M
RaDICaL(log)* [18]	80.0	1.7M
MobileNetv2* [19]	85.1	2.23M
ResNet50* [20]	84.08	23.5M
VGG16* [21]	50.0	33.6M

*Implemented as a 2-class classifier [18]

Comparison of accuracy and number of parameters for the object classification stage

That's a Wrap 🌯

✅ Novel framework using super-resolution for radar based object detection.
✅ Object detection using a combination of simulated and real radar data.
✅ Ideal candidate for low cost embedded applications.

Limitations.
❌ It's a two-stage framework rather than an end-to-end trainable network.
❌ It's not yet implemented on a hardware platform.
❌ Since the radar data is sparse, the dataset is highly imbalanced.

Code, dataset and supplementary material are on:

GitHub https://github.com/kanishkaisreal/DLSR_CRUW


IT AIN'T MUCH
BUT IT'S HONEST WORK