Improving Millimeter Wave Radar Perception with Deep Learning

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1. Introduction and Project Descriptions

Since the past few years, AI-Powered autonomy revolution in the automotive industry has attracted great attention worldwide. It is believed that in the not-too-distant future, fully autonomous vehicles will be the norm rather than the exception, redefining mobility in our daily lives. With deep learning widely applied on sensor data, self-driving cars are able to localize and map objects, understand the environment, and make correct decisions. As the most fundamental task, previous works have demonstrated accurate object detection and classification, but they are limited to data obtained from LiDARs and cameras. These optical sensors have high imaging resolution, but they naturally fail in low visibility conditions such as fog, rain, and snow, because light beams are narrower than water droplets and snowflakes.[?] This fundamental limitation of optical sensors is one of the major roadblocks to achieving the 5th SAE level of full automation. [?]

On the contrary, Radar has desirable propagation characteristics through small particles and can provide an alternate imaging solution in such inclement weather. Besides, radar can also directly measure the velocity of objects with the doppler shift of reflected signal without going through cluster tracking across frames. Although the low resolution of traditional automotive radar overshadows its advantages, the advent of Millimeter-wave antenna array technology provides an opportunity to have a reliable imaging system in inclement weather with higher resolution at the same time. Along with good propagation characteristics, it also provides huge bandwidth and large-aperture antenna arrays. This enables accurate Time-of-Flight (ToF) and Angle-of-Arrival (AoA) estimation for imaging. However, we would like to push the resolution to be comparable to that of LiDAR which has been proved to be relibale, but the imaging resolution in Millimeter-Wave is still not high enough to allow for applications like object detection or scene-understanding. Moreover, with RF one faces the issue of specularity, where reflections from objects may not come back to the receiver depending on the angle of incidence of the transmitted signal. Therefore, in this project, we propose to develop techniques that can enable high resolution imaging in low visibility conditions with RF signals. Our goal is to use deep learning models to enhance the low resolution images obtained from Millimeter wave radars, and enable various crucial vision applications for autonomous vehicles like lane detection, image mapping, localization, and object identification.

2. Challenges

Specularity is a challenge
New application
Dataset Experiment Processing
3D CNN
3D GAN size complexity
Evaluation

3. Method

Describe the overall method on how you solve the proposed problem, and a bit of original derivation that has some relevance to what youre trying to accomplish

Problem statement: low blured images no boundary can be seen, specularity causes missing parts, no availbale dataset, 4D CNN NN complex.

Overview 3D, in the method, we say that we start with 2D version, and based on that build 3D. We are trying to use cGAN to generate higher resolution images from low resolution radar images, which should have a sharp and accurate boundary of the object. Also, the missing parts due to specualarity of reflection need to be feel up. S

cGAN: Why cGAN: 1. GAN is tranfering images from 1 domain to another, some application Generative Adverserial Networks (or GANs) have been widely used to generate images [cite some stuff here]. In our case, we are looking to generate images with accurate boundaries using low resolution images as input. Conditional GANs have already proven successful in similar settings, such as in [1], where the authors have used thermal images under low light conditions to retrieve the human face boundaries and estimate is orientation. The other motivation behind using GANs is that generic loss functions such as the L_1 and L_2 (i.e. A loss function that tries to minimize the Euclidean or L_1 distance between the input and the output) render blurry images, which are not suitable for our application. As mentioned earlier, there are several factors that contributed to the input image being of low resolution, making the choice of the loss function more difficult.

CGANs take as input a Transition: cGAN has input, groundtruth, G, D

Input: Low resolution radar images, because there is no available public dataset of mmWave radar images, and collecting a big enough dataset by ourselves is not possible. We synthesized radar images. This heat-map is fed into the network. Groundtruth: 1. Size of 3D which makes the training phase very slow even when using GPUs. 2. 2D: 3. 3D

The input to our problem is pre-processed radar data. First, using the raw data from the antenna array, a coarse heat-map of objects are generated. After some further processing.

Why not raw data: (Goes to detail of Dataset jayden) Radar imaging processing algorithms is a well establish feild for 70 years. and there is fruitless to try and learn them using machine learning. So instead of The reason why we did not choose the raw data as input is twofold.

3.1. Conditional GAN

3.2. Dataset Generation

Challenge of unavailable radar dataset.

Experiment to collect radar images size time umbiguity

Simulation with EM

3D

2D Mask R-CNN input: radar image groundtruth: mask pros: large dataset with car truck human cons: No 3D info, no specularity 3D CAD input: contour groundtruth: pros: small dataset, single element cons: 3D shape info, specularity

Evaluate the simulation with EM simulation Feko and experimental results.

4. Experimental Results

Describe the setup of the experiments you ran, e.g., what evaluation metrics, datasets are used. Present the results, preferably in the form of tables and/or figures

4.1. Dataset

4.2. Results

5. Discussion and Conclusion

Analyze the results, summarize the findings and point out possible future directions

References

[1] I. M. H. K. A. V. V. P. R. B. A. U. Nambi, S. Bannur and B. Raman. Demo: Hams: Driver and driving monitoring using a smartphone. *ACM MobiCom*, 2018. 1