Millimeter-Wave Imaging for Self-Driving Cars

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1 Introduction

This proposal attempts to bring mmWave imaging to the repertoire of existing sensing technologies in autonomous vehicles. Currently, autonomous vehicles obtain 3D images of the environment using LiDAR [1] and cameras, which together provide accurate perception in most scenarios. However, since both these sensors rely on the optical wavelengths, their image quality deteriorates in low visibility conditions such as fog, smog, and snowstorms [2, 3, 4]. This limitation in severe weather conditions presents an important hurdle to achieving the vision of *fully* autonomous vehicles [5, 6]. Millimeter wave frequencies offer more favorable propagation characteristics in such inclement weather, due to their better penetration properties. Hence, mmWave imaging is essential for detecting obstacles and cars in scenarios that are unfavorable to LiDAR and cameras.

Car manufacturers today, such as Tesla, Honda, and Ford, are already using mmWave radars in their cars [7, 8, 9, 10] for adaptive cruise control [11] and collision avoidance. However, these systems only perform unidirectional ranging to determine the distance of the vehicle in front. They transmit FMCW (Frequency Modulated Continuous Wave) signals using forward facing directional beams that enable estimating the distance to a reflector. Extending this to imaging, entails steering the beam along all spatial directions to create a complete view around the car. However, scanning all directions can incur prohibitively high latencies since wideband FMCW sweeps typically have a duration of about 2ms [12, 13]. Hence, it can lead to few seconds of delay between consecutive images which is unacceptable for time-critical events associated with autonomous cars.

In order to enable practical mmWave imaging for autonmous cars, we propose to design a fast imaging algorithm. Our algorithm exploits the key observation that mmWave reflections are sparse in the 3D image space [14], [15]. We build on our group's past work on sparse recovery algorithms [16, 17] to design a new mmWave imaging system that can image cars and obstacles without scanning the entire space using a sublinear number of measuremente. Thus, instead of using $O(n)$ measurements to scan the space, we only need $O(\log(n))$ where n is the total number of beam directions. This would enable generating a mmWave image of the environment, while incurring low latency.

However, in order to realize a working real-time system, we will need to address other practical challenges. mmWave signals experience mirror-like specular reflections, causing only a few points on an object to reflect signals back to the receiver, producing an incomplete image. In order to tackle this, we make use of multiple FMCW sweeps at three different frequency bands (24 GHz, 60 GHz and 77 GHz), and combine snapshots of objects across both time and frequency to create coherent 3D images. The use of multiple frequency bands also helps increase the resolution of our imaging system, since the FMCW sweeps can be stitched across the different frequency bands to create a *virtual* sweep of much larger bandwidth.

Platform and Evaluation: We will implement our proposed system using three mmWave radios shown in Fig. 1(b) and Fig. 1(c). We have built an FMCW imaging radar both at 60 GHz and 24 GHz with a custom-built steerable phased array. For the 77 GHz, we will use the Texas Instruments IWR1443 Evaluation Module [18]. We have tested this current setup for imaging using the naive sequential scan approach. We compare the performance of our preliminary mmWave imaging system with that of a laser ranger[1]in section 5. We show that while both perform well in clear visibility conditions, the laser ranger gives erroneous readings in low visibility conditions (with artificial fog), whereas our mmWave imaging system is hardly affected.

This proposal will develop and build a fully working mmWave imaging system, integrated with the sublinear imaging algorithm that we propose. In doing, so we will address the above challenges and we will build upon our group's previous work on fast beam alignment for mmWave communication [19], sparse recovery algorithms [16, 17, 20] and sensor fusion [21, 22, 23].

2 System Overview

Fig. 1(a) shows an overview of our proposed system. The RF Front End uses FMCW at three different frequency bands (24 GHz, 60 GHz and 77 GHz) for robust imaging. The received signal is fed into the Sub-

[1]The laser ranger is used as a proxy for LiDAR, since both rely on observing laser reflections from objects for ranging.

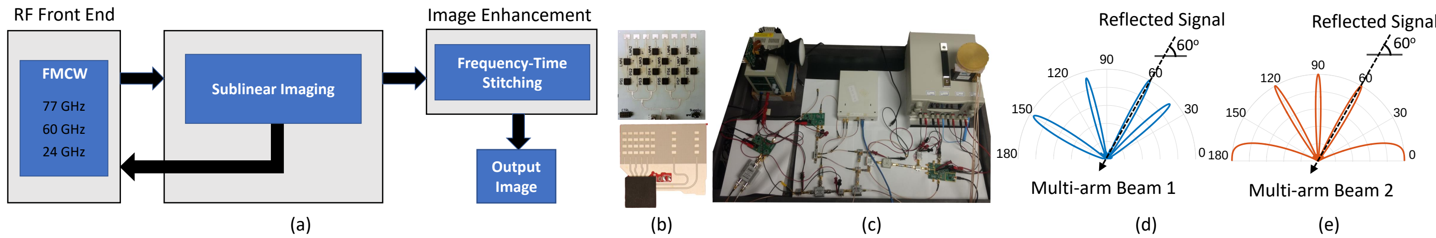

Figure 1: (a) System Overview (b) 24GHz, 77GHz antenna (c) 60GHz Hardware Setup (d-e) Multi-armed beam patterns

linear Imaging Algorithm. Based on the received signals, the algorithm provides feedback to the RF Front End about the optimal beam pattern for subsequent measurements. After collecting sufficient number of measurements to estimate the distance and direction to each reflector, the Sublinear Imaging Algorithm passes on the data to the Image Enhancement module, which combines information across time and frequency to produce enhanced images.

3 Sublinear Imaging Algorithm

From the transmitted and received signal, we can estimate the distance and velocity of all objects that reflected the transmitter's signal back to the receiver. However, in order to image the environment we also need to know the direction along which the reflected signals from each object was received. Instead of scanning, our algorithm uses multi-armed beams shown in Fig. 1(d) that can sample measurements from multiple directions simultaneously. This enables us to hash the beam directions using a few carefully chosen hash functions. We then identify the correct alignment by tracking how the energy changes across different hash functions.

Our algorithm is best understood through an example. Consider Fig. 1(d), where the multi-armed beam pattern is as shown, and the reflected signal arrives only along the 60° direction due to channel sparsity in mmWave. While the received signal alone is sufficient to estimate the distance and velocity of the corresponding reflector, we cannot uniquely determine if the reflector is along 40°, 60°, 110°or 150°, with respect to the receiver. However, this ambiguity can be resolved by using another multi-armed beam shown in Fig. 1(e). In both measurements we see the same reflected signal, and 60° is the only common direction in the two beam patterns.

While the above shows a simple example, we will design an algorithm that can handle more complex scenarios with more reflections. We will also exploit the sparsity along the range and velocity dimentsions to further enhance our algorithm. In particular, since we do not expect objects to have the same distance and the same velocity in real-life settings, we can use the sparsity in these supplementary dimensions to isolate the reflections with even fewer measurements.

4 Image Enhancement

This module improves upon the resolution of images obtained from the `Sublinear Imaging Algorithm` module. The resolution of FMCW imaging is limited by the bandwidth of the frequency sweep, and generating a sweep of arbitrarily large bandwidth is challenging. Therefore to obtain high resolution images, we stitch together the received FMCW sweeps across the three different frequency bands by compensating for the phase offsets between the sweeps. Using this, we create a *virtual* FMCW sweep that spans a much larger bandwidth, potentially providing a three-fold improvement in resolution.

For specularity, we exploit both the inherent mobility associated with vehicles and the multiple frequency bands. In particular, we segment the reflections that we obtain across time and frequency from different portions of an object, align them across snapshots while accounting for the relative motion, and then combine the individual components to create the overall image. The final enhanced image output will then be passed on to the AI system of the self-driving car for accurate scene understanding and decision making.

5 Initial Ground Work

■ **Experimental Setup**: As a starting point we have a mmWave system that performs imaging via sequential scans. We compare the performance of our experimental setup (Fig. 1(c)) with a laser ranger [24] in both clear visibility conditions and in artifical fog generated using a fog machine [25]. In this experiment, we attempt to image two metal reflectors and a person in a garage (Fig. 2(b)). We mount the laser ranger on a

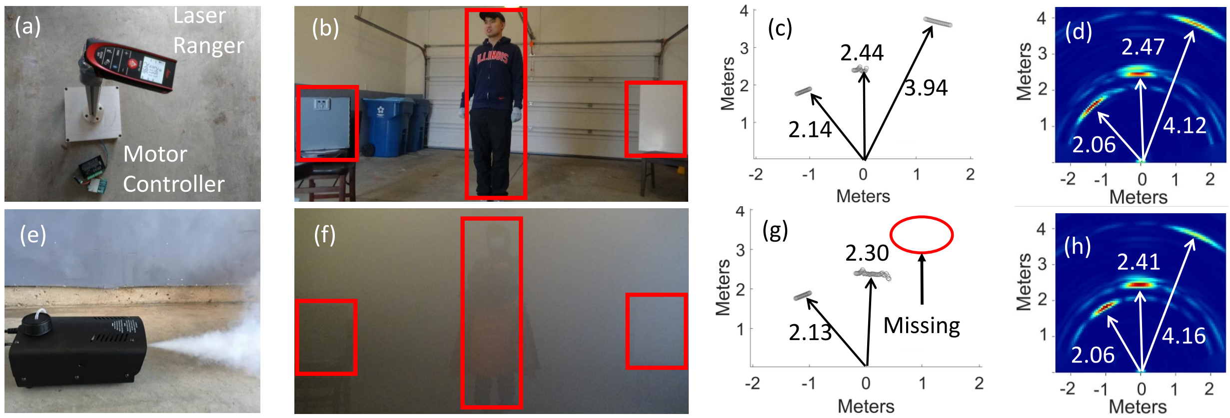

Figure 2: Comparison of ranging using laser and mmWave in clear conditions and after introduction of fog

stepper motor (Fig. 2(a)) that allows for a continuous 180° rotation to scan the room.

■ **Results**: Fig. 2(c) and 2(d) show the imaging results of the laser ranger and our system respectively, in clear conditions. Fig. 2(g) and 2(h) show the corresponding results in presence of fog. The results indicate that in fog both the camera and the laser ranger fail to image the farthest object, while our system is hardly affected. Further, as the fog intensifies, the laser ranger cannot image even the close by objects and simply traces a small circle around itself due to the severe scattering caused by fog. However, our system still shows minimal performance degradation even at high fog intensities. The images from the mmWave system are not very sharp since we are yet to implement the Image Enhancement algorithm described in Section 4.

■ **Video Demo**: We also include a video demo on our project website [26]. The demo shows a mobile Roomba carrying a metal object to be imaged. In clear conditions we observe that both laser and our setup track the object's motion accurately. However, with fog, the laser ranger stops giving readings after the object moves beyond 1.7 m from the laser ranger, whereas our setup can still track the object precisely. There is some observable lag between the object's motion and the mmWave image, but this is primarily due to the time consuming sequential scans. We believe that after implementing our sublinear imaging algorithm using multi-armed beams, we can have a truly real-time imaging system with mmWave.

6 Team Strength

Ashutosh is a 4^{th} year PhD student in Computer Science with several years of academic and industry research experience. With a strong systems background, he has over 6 publications in leading wireless systems conferences, and multiple awards including the R.T. Cheng Fellowship at UIUC. His recent work focuses on identifying liquids by analyzing wireless signals that pass through them, while his past work has centered around localization using multi-modal sensor fusion.

Suraj is a 2^{nd} year PhD student in Electrical and Computer Engineering with a background in signal and image processing, wireless communications and algorithms. His recent work focused on designing mmWave networks that enable dense spatial reuse, and currently he is working on desiging mmWave imaging systems for self driving cars. He has 3 papers under submission and has won the Cargill Global Scholarship during his undergraduate studies.

Both Ashutosh and Suraj graduated from IIT Bombay. Their CS and ECE skills compliment each other, which will enable them to see this project through to completion. They are both part of the Systems and Networking Research Group (SyNRG) at UIUC. The group is led by Prof. Haitham Hassanieh and Romit Roy Choudhury, who have a long track record in designing and build wirelss sensing and communication systems. See group website for more details: http://synrg.csl.illinois.edu/.

7 Project Horizon

We envision to complete this project within the next one year. First, we will converge on the algorithmic and design aspects of the system. Concurrently, we will also finalize the hardware platform with the phased-array antenna design to implement our sublinear imaging algorithm with multi-armed beams. We will conduct thorough experiments and testing, and consequently will deploy our testbed on vehicles to test our system in more practical settings.

References

[1] Wikipedia contributors. Lidar — wikipedia, 2018. https://en.wikipedia.org/w/index.php?title=Lidar&oldid=820540368.

[2] Perception in smoke, dust or fog. http://robotsforroboticists.com/perception-in-smoke-dust-or-fog/.

[3] Brian Yamauchi. Fusing ultra-wideband radar and lidar for small ugv navigation in all-weather conditions. In *Int. Soc. Opt. Eng.(SPIE)*, volume 7692, pages 1–10, 2010.

[4] Michael Barnard. Tesla and google disagree about LIDAR. Which is right? *Clean Technica*, 2016.

[5] Aarian Marshall. To let self-driving cars go anywhere, you must train them everywhere, Oct 2017. https://www.wired.com/story/waymo-self-driving-michigan-testing/.

[6] Neal E. Boudette. 5 things that give self-driving cars headaches. https://www.nytimes.com/interactive/2016/06/06/automobiles/autonomous-cars-problems.html, Jun 2016. https://www.nytimes.com/interactive/2016/06/06/automobiles/autonomous-cars-problems.html.

[7] Tesla. Tesla autopilot. https://www.tesla.com/autopilot.

[8] Ford. Adaptive cruise control and collision warning with brake support. *Ford Media Release*, 2012. https://web.archive.org/web/20131014210324/http://corporate.ford.com/doc/Adaptive_Cruise.pdf.

[9] Honda. Honda sensing. 2017. https://automobiles.honda.com/sensing.

[10] BMW. Bmw active driving assistant. https://www.bmwusa.com/vehicles/bmwi/bmw-i8/bmw-i8-features-and-specs.html.

[11] Autonomous cruise control system. *Wikipedia*. https://en.wikipedia.org/wiki/Autonomous_cruise_control_system.

[12] Analog Devices. *Direct Modulation/Fast Waveform Generating, 13 GHz, Fractional-N Frequency Synthesizer*, 7 2014. Rev. E.

[13] Texas Instruments. *15-GHz Wideband PLLatinum RF Synthesizer With Phase Synchronization and JESD204B Support*, 8 2017. Rev. A.

[14] E. Erkip. S. Rangan, T. S. Rappaport. Millimeterwave cellular wireless networks: Potentials and challenges. *Proceedings of the IEEE*, 2014.

[15] C. R. Anderson and T. S. Rappaport. Millimeterwave cellular wireless networks: Potentials and challenges. *In-Building Wideband Partition Loss Measurements at 2.5 and 60 GHz.*, 2004.

[16] Haitham Hassanieh, Piotr Indyk, Dina Katabi, and Eric Price. Simple and practical algorithm for sparse fourier transform. In *Proceedings of the twenty-third annual ACM-SIAM symposium on Discrete Algorithms*, pages 1183–1194. Society for Industrial and Applied Mathematics, 2012.

[17] Haitham Hassanieh, Piotr Indyk, Dina Katabi, and Eric Price. Nearly optimal sparse fourier transform. In *Proceedings of the forty-fourth annual ACM symposium on Theory of computing*, pages 563–578. ACM, 2012.

[18] Texas Instruments. *IWR1443 Single-Chip 76- to 81-GHz mmWave Sensor*, 8 2017. Rev. A.

[19] Haitham Hassanieh, Omid Abari, and et al. Agile millimeter wave networks with provable guarantees. *arXiv preprint arXiv:1706.06935*, 2017.

[20] Haitham Hassanieh, Lixin Shi, Omid Abari, Ezzeldin Hamed, and Dina Katabi. Ghz-wide sensing and decoding using the sparse fourier transform. In *INFOCOM, 2014 Proceedings IEEE*, pages 2256–2264. IEEE, 2014.

[21] Sheng Shen, He Wang, and Romit Roy Choudhury. I am a smartwatch and i can track my user's arm. In *Proceedings of the 14th annual international conference on Mobile systems, applications, and services*, pages 85–96. ACM, 2016.

[22] Nirupam Roy, He Wang, and Romit Roy Choudhury. I am a smartphone and i can tell my user's walking direction. In *Proceedings of the 12th annual international conference on Mobile systems, applications, and services*, pages 329–342. ACM, 2014.

[23] He Wang, Souvik Sen, Ahmed Elgohary, Moustafa Farid, Moustafa Youssef, and Romit Roy Choudhury. No need to war-drive: Unsupervised indoor localization. In *Proceedings of the 10th international conference on Mobile systems, applications, and services*, pages 197–210. ACM, 2012.

[24] Leica. *DISTO D2*. https://lasers.leica-geosystems.com/disto/d2.

[25] 1byone. Fog machine 400w. https://www.1byone.com/Stage-Lighting-Effects/Fog-Machines/O00QL-0047.

[26] Demo. http://synrg.csl.illinois.edu/QinF2018/.