A Review of Recent Advancements Including Machine Learning on Synthetic Aperture Radar using Millimeter-Wave Radar

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Abstract—In this paper, we review recent and emerging Synthetic Aperture Radar (SAR) applications using mm-Wave radar, ranging from concealed item detection to autonomous systems. Furthermore, relevant machine learning (ML) concepts are introduced and the review of ML applications in high-resolution mm-Wave SAR image enhancement and generation are presented. The paper is concluded with challenges and expectations of mm-Wave SAR imaging with emphasis on autonomous vehicles.

Index Terms—Millimeter Wave, Synthetic Aperture Radar, Generative Adversarial Networks, Convolutional Neural Networks, Autonomous Vehicles

I. INTRODUCTION

Autonomous Systems and Advanced Driver-Assistance Systems (ADAS) use a variety of sensors to achieve their tasks, ranging from optical sensors such as cameras and lidars, to Radio-Frequency (RF)-based sensors such as millimeter wave (mm-Wave) radars. However, the radars play a secondary role in environment sensing, and are generally limited to collision avoidance and braking systems, while the optical sensors are used to map the environment and other computer vision tasks, on account of its higher resolution compared to the RF counterparts. Synthetic Aperture Radar (SAR) have established superior imagery at night or through-the-cloud sensing, when traditional optical sensors would fail. However, SAR using mm-Wave sensors is a relatively new area of research that is still being explored for high-resolution imaging applications. The mm-Wave SAR has the potential to significantly enhance current autonomous systems, especially in cases where the failing of optical sensors has resulted in catastrophic crashes and loss of life while testing [1], [2]. In this paper, we present a review of the recent developments and applications of mm-Wave SAR and SAR image enhancement using applied machine learning, that could potentially develop mm-Wave radars for imaging applications.

The paper is organized as follows. In Section II, we present an overview of SAR fundamentals, followed by recent studies and applications using mm-Wave SAR in Section III. In Sections IV and V we review and present applications of applied machine learning to enhance SAR imagery. Discussion, challenges and future direction of mm-Wave SAR is summarized and presented in Section VI.

II. SAR FUNDAMENTALS

In SAR, the cross-range direction movement of physical antenna on the radar platform allows for coherent spatial processing in cross-range, so that the cross-range resolution is improved. In [3], there are two viewpoints as basic understanding of SAR principle: (i) From the synthetic aperture viewpoint as in Fig. 1 (a), the region of interest (ROI) during “focus time” as the radar moves, also called the SAR aperture time, can be viewed as an increased synthetic aperture size \( D_{SAR} \). As a rule of thumb, the angular resolution is inversely propositional to the antenna aperture size, therefore the angular resolution in cross-range is improved and so does the cross-range resolution; (ii) From the Doppler viewpoint as in Fig. 1 (b), the cross-range of static scatter points in different places are relevant to its Doppler with simple geometric relation. As a rule of thumb, the Doppler frequency resolution is inversely proportional to signal duration which is accumulated over the SAR aperture time, resulting in a finer Doppler resolution.

Basic SAR imagery algorithms, such as Dopper Beam Sharpening (DBS) and Range-Doppler Algorithm (RDA), directly come from the Doppler viewpoint. Specifically, the target range \( R(\mu) \) is a quadratic form of the relative position \( \mu \) between radar and the target scatter point. As the radar moves, the change of \( R(\mu) \) induces a linear frequency modulation on the phase of receiving signal, so that the cross-range frequency resolution is improved as the bandwidth-time product is increased. For simplicity, in DBS the mapping between the target position to a reference point and the cross-range frequency is approximated to be linear. This approximation causes quadratic phase error, and the target scatter point range \( R(\mu) \) is assumed to be in the same range bin over the whole

Fig. 1. SAR Principle. (a) Synthetic aperture viewpoint. (b) Doppler viewpoint.
SAR aperture time so the possible range migration of $R(\mu)$ is ignored. The RDA first does range interpolation to address the range migration, and then mapping from the cross-range frequency to the cross-range through de-chirping to address the quadratic phase error. Advanced algorithms, such as Chirp Scaling Algorithm and Range Migration Algorithm (RMA) [4], aim to address the range migration and quadratic phase error more accurately and efficiently.

III. RECENT TRADITIONAL MM-WAVE SAR APPROACHES

Traditionally radar systems were developed for commercial and defense applications and were cost and size intensive. However, development in fabrication techniques and patch antenna configurations, radio frequency integrated circuits (RFICs) technology have allowed for low-cost, low-size mm-Wave automotive radar transceivers, that serve as one of the primary sensors for autonomous systems. In this section, we review some interesting recent SAR applications that have been proposed employing these mm-Wave sensors.

A. mm-Wave SAR Models

In 2010, Feil et al. explored mm-Wave SAR for short-range surveillance and security applications [5]. A 4.8 GHz wide Frequency Modulated Continuous Wave (FMCW) configuration based 77 GHz stripmap SAR system was setup by mounting the sensor on a linear actuator, controlled using a remote computer. The setup was tested in an indoor scenario to image a double wing door (Fig. 2) and a 40 mm diameter aluminum sphere at 40 m, and achieved reliable detection when compared to background clutter, with the cell-averaging Constant False Alarm Rate (CFAR) threshold set at 10 dB.

A 90 GHz FMCW SAR onboard an Unmanned Aerial Vehicle (UAV) was studied by Scannapieco et al. in 2016, using a simulation approach, for indoor operations [6]. The simulator consisted of two components - (i) Scene Simulator, that takes in radar and scene parameters to generate the synthetic FMCW raw dechirped signal using ray-tracing algorithms, and (ii) Data processing unit that uses the dechirped signal and motion parameters to generate a 2-D focused data matrix. Apart from simulation data, the data processor would also work with real world data. Fidelity testing with both nonfluctuating and fluctuating targets were conducted and the reflection and geometry of the scene in the image was analyzed and presented. This work was aimed to help in assessing commercial FMCW mm-Wave sensors and aid in the development of motion-compensation algorithms for applications involving UAVs.

A portable mm-Wave 3-D imaging radar was proposed by our group (Zhang et al.) in 2017 [7], to pave a way for future autonomous systems to map terrains. The relative motion between the targets and the 77 GHz mm-Wave radar, moving in a circular track, is projected in different directions to obtain 2-D images from each range bin. The 3-D imaging from these 2-D images is achieved using inverse radon transform, similar to Computed Tomography (CT) reconstruction, was validated in a MATLAB simulation environment and tested with a MIMO radar and metal ball targets (Fig. 3). The hand-held rotation of radar caused inaccuracies that can be further alleviated with the use of an automated motion on tracks.

In 2019, Mohammadian et al. presented their study on SAR mm-Wave imaging by using a mono-static SISO configured 79 GHz FMCW radar, mounted on a scanning stage with two degrees of freedom [9]. The system was tested to detect a spiral metal target with 14 aluminum spheres, concealed weapon in a mannequin, and through-wall imaging by detecting metal pipes behind the wall. Another study for concealed item detection using 77 GHz mm-Wave FMCW radar was done by Yanik...
et.al. [8]. The radar module was mounted on a zig-zag 2-D scanning track which was controlled by a remote computer. A metal patch with cutouts was placed under various concealing scenarios and was imaged and detected by the system, as shown in Fig. 4, to show the high image quality performance that can be achieved with mm-Wave sensors.

In the recent past, Nguyen et. al have been investigating mm-Wave SAR for military applications. In 2019, a 35 GHz forward-looking SAR system (FLoSAR) was proposed to aid aircraft navigation in degraded visual environments [12]. The author identified critical challenges in terms of computational complexity, aliasing and motion compensation that needed addressing to deploy the system in practice. The author addressed the associated computational challenges by proposing a fast Back-Projection Algorithm (BPA) in 2020 [13], that offered a 118 fold improvement in execution time, over the baseline algorithm, on a CPU, and an additional 132 fold improvement by using a GPU. The authors also used Electro-Magnetic (EM) simulations to validate the proposed 3-D SAR system on a realistic landing zone, with the targets clearly detectable and resolvable in the constructed SAR image. However, the authors acknowledge that the simulations assume accurate measurement data from Inertial Navigation Systems (INS), and further investigation are to be conducted to study the practical effects of vibrations/motion anomalies of the platform, in the near future. In another 2020 paper, Mishra and Nguyen studied the Phase Gradient Autofocus (PGA) methods for FLoSAR in an attempt to address the motion compensation challenge that was previously identified [14]. The numerical simulations suggested ideal reconstruction of the target when there is no phase errors. However, while distortions and sidelobes caused by perturbations can be attenuated with PGA, the authors suggested continued investigation to further improve PGA for practical implementation of mmWave FLoSAR.

The mm-Wave SAR has also been explored using automotive radars. Kobayashi et.al presented a preliminary study on imaging and doppler effect for mm-Wave automotive SAR and showed that the method could achieve constant spatial resolution for distant locations, using simulated data [15]. A high-resolution 2-D SAR using 76.5 GHz FMCW radar was implemented and tested, by mounting on a vehicle by, Yamada et.al. [10]. The squint-mode SAR (55°) imaged the scene containing a trihedral reflector, guard rail, rubber pole, traffic sign and a dummy pedestrian. The image was generated using back-projection that yielded sharper image when compared to real-aperture image without SAR, shown in Fig 5(a). In 2019. Oshima et.al. investigated the performance of automotive mm-Wave SAR, using backprojection, when the vehicle carrying the radar moved in a curved track [11]. The approach was verified by imaging a parking lot, shown in Fig 5(b), and a side-walk using a 76.5 GHz radar mounted on a vehicle. The authors aimed to follow up those preliminary results with a more comprehensive quantitative evaluation in the near future.

B. Compressed Sensing Based Approaches

Our group (Zhang et.al) extended our prior work [7] to improve resolution by incorporating a Compressed Sensing (CS) approach [17]. The radar is mounted on a circular track where the fast-time-slow-time-angle data is eventually converted to range-azimuth-elevation field-of-view using inverse radar transform, and calibration matrices obtained using an $l_1$ minimization on the sensing basis and representation basis in CS. The approach was simulated and tested on four metal targets using a 76.5 GHz FMCW mm-Wave radar with a 1 GHz bandwidth, with the platform rotating in a 60 cm radius track at 0.2 s per round. The advantages of the method included flexibility on data reconstruction due to CS, higher SNR and faster data acquisition, albeit at the expense of higher signal processing time. Another CS based high resolution mm-Wave SAR was proposed by Jung et.al. in 2018 [16]. The aim was to reduce the computation time by using a greedy approach to solve CS iteratively. A 75-110 GHz high-gain horn antenna was used for evaluating the proposed approach on a gun shaped metal target (Fig. 6). While achieving similar integrated side-lobe ratio, the proposed algorithm achieved ≈45% savings in computational time compared to Orthogonal Matching Pursuit (OMP) applied RMA [18].

IV. APPLIED MACHINE LEARNING FUNDAMENTALS

With the advent in high performance computing and parallel processing units, machine learning (ML) has gained significant recognition in several automation and enhancement applications, including (but not limited to) Bayesian models, Support Vector Machines, Principal Component Analysis (PCA) and the extremely popular Neural Networks and Deep Learning [19]–[22]. In the interest of the scope of this paper, we present a concise background on Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) to understand and explore emerging ML aided SAR applications.

A. Convolutional Neural Networks

Neural Networks are composed of computational units, or “artificial neurons” that take in a weighted input and produces an output subject to a non-linear activation function. This non-linearity allows neural networks to deduce complex boundaries
in order to aid classification and regression problems. CNNs are a class of neural networks that are primarily used on image inputs. CNNs make use of an $N \times N$ unit kernel, that is slid across the image where the aforementioned weighted input-non-linear output operations are performed, at a lower complexity than traditional feed-forward neural networks. CNNs learn spatial features in an image more adequately than traditional feedforward networks through convolution, and have also been explored in the realm of SAR applications.

Several ML based SAR applications have been developed, ranging from target classification to image enhancement [24]–[27]. We will look at GANs in mm-Wave SAR. GANs have in the recent past found several applications in SAR. The authors accounted their models’ superior adaptation to large-scale dataset and DeepSAR-F’s training methodology for the ≈ 99.5% accuracy on the MSTAR dataset.

A 2019 article by Ma et al. also used CNNs, fused with superpixel algorithm, for land cover classification from polarimetric SAR images [30]. The proposed framework consisted of two branches - (i) Superpixel: contour/superpixel structure extraction by taking in Pauli decomposed RGB PolSAR image following a simple linear iterative cluster scheme, and (ii) CNN: segmented image retrieval by taking in a six-channel complex value coherency matrix from Pauli decomposition. The outputs were then fused together to compensate for the misclassification of boundary pixels, and the occasional singular pixels within the boundary that ideally should be homogeneous. The proposed fusion framework was tested on four distinct open-source PolSAR datasets, achieving ≥98% accuracy on three and ≈95% on the fourth dataset, respectively. While achieving highly accurate classification offline, as shown in Fig. 8, the authors however acknowledged the high computation time for the overall fusion framework which makes it unsuitable for real-time classification.

A Robust PCA (RPCA) based stripe artifact removal for mm-Wave automotive SAR was presented by Shan et al. in 2019 [31]. A squint-mode Single Input Multiple Output (SIMO) mm-Wave SAR image was synthesized using BPA, which suffers from stripe shaped artifacts that can significantly degrade obstacle detection tasks, as shown in Fig. 9. A 76.5 GHz Linear Frequency Modulated (LFM) signal was used to collect the data and the BPA aided SAR synthesized image was then decomposed into stripe artifacts (low-rank component) and significant obstacles (sparse component) using RPCA, while using Alternating Direction Method of Multipliers (ADMM) to solve the convex optimization problem.

Fig. 7. An overview of GAN architecture

### B. Generative Adversarial Networks

Generative ML models try to generate new data that follow the distribution of the desired data-set. GANs are a class of these generative models that are trained by using an adversarial discriminator network [23], shown in Fig. 7. The generative network $G$ takes in a random noise vector $z$ to generate an instance $G(z)$ following a distribution $p_z$, which is aimed to represent the real data distribution $p_{\text{true}}$, which is known apriori to the adversarial discriminatory network $D$. The adversarial network’s objective is to correctly classify if the generated instance is “fake”/synthetic or if it belongs to the true distribution. The model is trained with a min-max loss function $V$, given by:

$$
\max_D \min_G V(D, G) = \mathbb{E}_x [\log D(x)] + \mathbb{E}_z [1 - \log D(G(z))]
$$

where, $\mathbb{E}[]$ is the expected value function. The first term represents the contribution of the discriminator, which is intended to be maximum for the discriminator to predict the true identity of the generated data. The second term represents the generator’s contribution which is intended to be minimum in order to “trick” the adversary. The generator model’s training is complete when the adversarial discriminator is no longer able to distinguish between the generated data distribution and the true class distribution, i.e discriminator accuracy=50%. GANs have in the past found several applications in forgery detection, domain transfer, and super-resolution image enhancement [24]–[27]. We will look at GANs in mm-Wave SAR application in the following section.

### V. APPLIED MACHINE LEARNING IN SAR

In the recent years, several ML based SAR applications have been developed, ranging from target classification to image enhancement. In 2017, Li et al. proposed DeepSAR-Net for SAR automatic target recognition (ATR) [28]. The authors developed two CNN based architectures, with a different learning approach, viz. (i) DeepSAR: trained on the dataset by using random initialization on the entire network, and (ii) DeepSAR-F: trained by initializing the network with a pre-trained model on a large dataset with the exception of the randomly initialized fully connected layer. The models were evaluated its performance on the MSTAR dataset, which was obtained using a 10 GHz SAR in spotlight configuration with a 1 ft resolution [29]. The models were developed to be tested on three target identification and ten target identification scenarios and compared with the state-of-the-art ATR techniques. While DeepSAR-F outperformed the other models marginally for the three target scenario, both DeepSAR and DeepSAR-F showed significant improvement in accuracy in the ten target scenario.
The RPCA method was applied to three SAR images with squint angles of 0°, 45°, and 70°, by dividing the time series image into 100 segments (each 1 m along the track) to cover the overall 100 m along the track. The method provided superior performance compared to the traditional ADMM approach and the sparse component in the results clearly highlighted obstacles with the stripe artifacts removed.

The image enhancement capabilities of GANs have also been explored in SAR imaging applications. Wang et al. proposed SAR-GAN in 2018, that aimed at generating high-quality visible-like image from a SAR image input [32]. The primary motivation to overcome the interpretability of SAR images due to (i) speckle noise contamination and (ii) lack of color information. The SAR-GAN architecture had three main components - first, a single residual layer, deep CNN despeckling network that takes in the raw SAR image; second, a multi-layer encoder-decoder CNN that takes in the despeckled SAR image for colorization; and third, an adversarial discriminatory model that tries to predict if the generated colorized image belongs to the true distribution or not. The SAR-GAN architecture was trained and evaluated by simulated SAR imagery obtained from Google Maps Satellite images, as shown in Fig. 10. The trained model was tested on the simulation data, as well as ground testing with the 60 GHz SAR (for input data) and Stereo camera (for the ground truth) on real cars, including scenarios with fog/rain occluding the targets as shown in Fig. 11. HawkEye provided encouraging results in terms of accurate ranging and size/orientation/shape of the car. However, the authors acknowledged that the performance degrades with multiple cars in the scene, and the computational intensity made HawkEye unsuitable for real-time applications at this instance.

VI. DISCUSSION, CHALLENGES AND FUTURE DIRECTION

In this paper we reviewed some recent developments in mm-Wave SAR applications, and the role of machine learning techniques to enhance SAR capabilities. The reviewed applications show the advantages of mm-Wave radars in detecting concealed items, that are traditionally undetected by optical sensors. Such systems can find applications in airport security and package mailing security services. The results also show potential in mm-Wave radars for imaging applications which can be used in autonomous system, especially to assist the traditional optical sensors in scenarios when cameras fail during low-light, rain, snow or foggy environment. The mm-Wave SAR also has the capability of seeing through obstacles, which is extremely critical for timely pedestrian detection and avoid unforeseen accidents. The mm-Wave SAR can also be used to map the scene and identify curbs, roads and other vehicles to assist applications such automated valet parking.

However, mm-Wave SAR image resolution is still low to be directly used for traditional object classification applications. Overcoming this challenge can be done in either of the two stages, (i) Pre-SAR, and (ii) Post-SAR, or a combination of both. Pre-SAR comprises of traditional radar signal processing
approaches to generate the SAR imagery. Improving resolution in Pre-SAR would either require more antenna channels and/or a larger synthetic aperture size. While antenna channels are size intensive, generating a larger synthetic aperture would require a longer data capture time and is computationally and time intensive, which are unsuitable for real-time applications. Post-SAR refers to image processing or machine learning aided resolution enhancement of the obtained SAR imagery, generally in a supervised manner using a parallelly obtained high-resolution image of the same scene using an optical sensor. The primary challenge in Post-SAR enhancement is the lack of available mm-Wave SAR data-sets, along with the ground truth, that could aid in the development of the machine learning architectures. Furthermore, Post-SAR approaches depend heavily on radar hardware and parameters, i.e. a machine learning model would only support that specific radar, whose SAR images have been used in the training process.

Using SAR imaging at a higher frequency band, such as Terahertz (THz) could reduce the size of the antennas further, allowing more channels to be integrated in the transceivers. Furthermore, highly-parallel computation and processing units could be used to address the time intensive SAR data acquisition and processing. Finally, open-source data-sets would immensely help the scientific community to develop effective and efficient algorithms to further improve mm-Wave SAR imaging, in the future.

REFERENCES


