Airborne Radar Forward-Looking Imaging Algorithm Based on Generative Adversarial Networks

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Abstract

Radar forward-looking imaging is gaining significance due to its convenience in various applications like battlefield reconnaissance, target surveillance and precision guidance. Although synthetic aperture radar (SAR) techniques are commonly used to achieve high azimuth resolution, they suffer from limitations in forward-looking area due to the poor Doppler resolution and the “left-right” ambiguity problem. In recent years, generative adversarial networks (GANs), a common deep learning approach that produces excellent results in image motion blur removal, has been extensively used. This letter proposes building an end-to-end forward-looking imaging network using GAN to produce high-resolution images, which increases the efficiency and quality of imaging. Compared to conventional forward-looking imaging methods such as the deconvolution-based methods, this algorithm eliminates the design and iterative processes of the observation matrix. Simulated and real radar data verified that this approach offers robust recovery and better performance.
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Radar forward-looking imaging is gaining significance due to its convenience in various applications like battlefield reconnaissance, target surveillance and precision guidance. Although synthetic aperture radar (SAR) techniques are commonly used to achieve high azimuth resolution, they suffer from limitations in forward-looking area due to the poor Doppler resolution and the “left-right” ambiguity problem. In recent years, generative adversarial networks (GANs), a common deep learning approach that produces excellent results in image motion blur removal, has been extensively used. This letter proposes building an end-to-end forward-looking imaging network using GAN to produce high-resolution images, which increases the efficiency and quality of imaging. Compared to conventional forward-looking imaging methods such as the deconvolution-based methods, this algorithm eliminates the design and iterative processes of the observation matrix. Simulated and real radar data verified that this approach offers robust recovery and better performance.

Introduction: Currently, synthetic aperture radar (SAR) or Doppler beam sharpening (DBS) technology is commonly used for radar imaging on moving platforms to achieve high azimuth resolution [1]. However, these methods are not suitable for forward-looking imaging due to the negligible difference in Doppler frequencies between scatterers in the forward-looking area [2]. Consequently, the forward-looking area is known as the "blind" area for SAR and DBS due to the significant decline in resolution. To address this, scanning radar system combined with the real aperture imaging method is employed for airborne or missile-borne radar forward-looking imaging. However, the azimuth resolution of the real aperture imaging method is constrained by the physical aperture size. While theoretically, by increasing the physical antenna aperture the azimuth resolution can be enhanced, this is practically constrained by the size of the platform, particularly for airborne and missile-borne radar systems. To solve this problem, various forward-looking imaging algorithms have been developed, including the monopulse imaging method [3], deconvolution-based approaches [4], and many others. Deep learning has recently been introduced to radar signal processing and has shown good performance in classification [5], detection [6], and imaging [7]. However, studies on using deep learning for radar forward-looking imaging are rare to date. Forward-looking imaging is a convolution model but the deconvolution problem is ill-posed due to noise and low-pass characteristic of antenna pattern function. Generative adversarial networks (GANs) can solve this issue by learning data distribution and enhancing robustness, improving accuracy and robustness of forward imaging. GANs was first introduced by Goodfellow in 2014 [8]. In 2017, Legid proposed the GAN for super-resolution (SRGAN) [9] to achieve better visual effects in reconstructed images, but they still contained artefacts. To address this, Wang et al. proposed an enhanced generative adversarial network for super-resolution (ESRGAN) [10] based on the SRGAN model. They used residual-in-residual dense blocks (RRDBs) [10] as the fundamental unit for network feature extraction, and incorporated the relativistic discriminator as the model of discriminator. The improved ESRGAN model enhances the visual quality of reconstructed images and the capacity to reconstruct model details.

Inspired by image motion blur removal and the use of GAN in image super-resolution, this letter propose a GAN model for radar forward-looking imaging. The proposed model is based on a dual-scale discriminator with the feature pyramid network (FPN) [11] as the central module of the generator. To strengthen the network's backbone, we employ Inception-ResNet-v2. Both simulations and real radar data processing demonstrate a significant improvement in image resolution compared to the real beam imaging method.

Proposed method: Figure 1(a) depicts the structure of the generator which adopts the FPN structure to better extract image features. The shortcut branch of the original map is added to the feature outputs of each of the five branches, which are then fused depending on the upsampling procedure. The generator includes nine residual modules, two deconvolution modules, one tanh convolution module, two 1/2 convolution modules, and one normal convolution module. Each residual module comprises convolution, instance normalization, and a Relu module, followed by a dropout regularization of 0.5 probability. The generator initiates the process by executing a boundary expansion on the input image, which possesses dimensions of 6 pixels in both width and height. Subsequently, it undergoes a convolution operation with a 7x7 kernel, followed by a Batch Normalization (BN) operation, which is subsequently normalized. Upon completion of these processes, a Rectified Linear Unit (ReLU) activation function is applied. The resulting output image retains dimensions identical to those of the input, thereby maintaining consistency in size throughout the procedure. The discriminator consists of two components: a global discriminator and a local discriminator. The global discriminator takes the entire image as input, while the
local discriminator takes an arbitrarily cropped portion of the image as input. Both discriminators perform convolution operations on the input image and output a number representing the probability that the input image is real. Figure 1(b) illustrates the architecture of the discriminator.

The loss function comprises two components: Wasserstein GAN-loss [12] and content-loss. WGAN-loss regulates the ability of the discriminator to distinguish between real and fake images, while content-loss controls the quality of the features used to generate the image. Training the original GAN model (vanilla GAN) is challenging because it is susceptible to issues such as gradient disappearance and mode collapse. WGAN [12] was proposed to overcome this challenge by using the Wasserstein-1 distance, simplifying the training process. WGAN-GP, which requires minimal hyperparameter adjustment, enables stable training across a range of GAN configurations. For this study, we use WGAN-GP, and the adversarial loss is calculated as follows:

$$L_{GAN} = \sum_{n=1}^{N} -D_{\theta_n}[G_{\theta}(I^n)]$$

The content-loss measures the difference between the original and generated images. There are two commonly used options, L1-loss (also known as MAE or absolute error) and L2-loss (also known as MSE). Recently, a novel approach called perceptual loss has been introduced. This method employs an L2-loss that evaluates the dissimilarity between the feature maps generated by CNN and the corresponding ground truth feature maps, thereby providing a more perceptually relevant measure of image quality. The definition of perceptual loss is as follows:

$$L_{p} = \frac{1}{W_{i,j}H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} \left\{ \Phi_{i,j}(I^x)_{x,y} - \Phi_{i,j}[G_{\theta}(I^n)]_{x,y} \right\}^2$$

where $W_{i,j}$ and $H_{i,j}$ signify the dimensionality of the feature map and $\Phi_{i,j}$ signifies the feature map produced by the $j_{th}$ convolutional layer (after activation) prior to the $l_{th}$ max pooling layer after feeding the picture into VGG19 (pre-trained on ImageNet).

Currently, it is a changing work to obtain forward-looking imaging datasets with high-resolution labels due to the limitation of existing radar forward-looking imaging method. To overcome this challenge, we utilize existing high-resolution Synthetic Aperture Radar (SAR) images as the ground scene to generate simulated echo datasets that are employed in the training of network. The dataset comprises multiple grayscale image pairs, and Figure 2 displays the processing flow of the data.

Simulation and real data processing results: This section presents simulation data and real data processing results to demonstrate the feasibility of the proposed forward-looking imaging algorithm.

Firstly, simulation of point-target imaging using the proposed algorithm is conducted. The major parameters are listed in Table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wavelength</td>
<td>0.02m</td>
</tr>
<tr>
<td>Beam Width</td>
<td>2°</td>
</tr>
<tr>
<td>Beam scanning velocity</td>
<td>100°/s</td>
</tr>
<tr>
<td>Beam scanning scope</td>
<td>-20°~20°</td>
</tr>
<tr>
<td>PRF</td>
<td>2000Hz</td>
</tr>
<tr>
<td>Radar platform velocity</td>
<td>0 m/s</td>
</tr>
<tr>
<td>Total number of point-targets</td>
<td>50</td>
</tr>
</tbody>
</table>
As shown in Figure 3, the convolution of the antenna pattern causes each point target to spread in azimuth, leading to poor resolution in the real beam image. After being processed by the proposed network, each point target is reconstructed more accurately, resulting in higher resolution in the azimuthal direction.

To further verify the imaging performance of the proposed method, the simulation results of ground scene is provided, in Figure 4(a). The simulated data is generated from a high-resolution SAR image, and note that this data was not included in the training set. Figure 4(b) provides the imaging result of proposed method. By comparing them, it is clear that the azimuth resolution is improved, thus validating the capability of scene recovery of the proposed method.

At last, we applied the network to a group of real data collected by a X-band radar system to verify its feasibility in practice. The major parameters are listed in Table 2.

### Table 2. Parameters of the Measured Data.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band</td>
<td>X band</td>
</tr>
<tr>
<td>Beam Width</td>
<td>4°</td>
</tr>
<tr>
<td>Beam scanning velocity</td>
<td>300°/s</td>
</tr>
<tr>
<td>Beam scanning scope</td>
<td>-10.5°~10.5°</td>
</tr>
<tr>
<td>PRF</td>
<td>10MHz</td>
</tr>
<tr>
<td>Radar platform velocity</td>
<td>100 m/s</td>
</tr>
<tr>
<td>Flight altitude</td>
<td>4000m</td>
</tr>
</tbody>
</table>

In Figure 5, images of the real data by using the real beam imaging method and the proposed algorithm are provided, where zones with a same isolated target in the two maps are enlarged to compares the performance of the two methods in detail (see the red boxes). It is clear that the proposed method overperforms the real beam imaging method, both in terms of the resolution of the entire image and the resolution of the isolated point-like targets.

**Conclusion:** A novel method for forward-looking image super-resolution is proposed in this letter. Compared to the real beam imaging method, the images restored by the trained model in this paper achieve a better performance on both simulated and real scenarios.

### References