An Echo Intensity Calculation Method based on DNN for SAR Ray-tracing Simulation

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Abstract

The calculation of echo intensity involved in the SAR image simulation is usually based on the electromagnetic formula or approximate formula derived under certain assumptions. However, the parameters used in these formulas are often difficult to obtain, and the formulas have errors with the actual situation. In this paper, a method of embedding deep neural network (DNN) into the simulation process based on ray tracing is proposed, so that the DNN model can be directly used to fit the calculation formula of echo intensity from real SAR images. Simulation results show that this method can obtain SAR images with high similarity.

Keywords: deep neural network; differentiable rendering; electromagnetic scattering modeling; ray tracing; SAR image simulation

1 Introduction

SAR image simulation can quickly provide a large number of images of a target under different imaging conditions at a low cost, and it has been applied in many application fields, such as target classification, building height inversion, and SAR image interpretation.

There are usually two main problems to be solved in SAR image simulation. One is to determine the location of the echo in the range-azimuth image domain. The other is to calculate the strength of the echo. Geometrical optics (GO) and ray tracing techniques are commonly used to calculate the location of the echo. The physical optical (PO) method or approximate physical electromagnetic formula is used to calculate the echo intensity [1].

However, PO and approximate physical electromagnetic formulas have some problems in the actual simulation. First, the accuracy of these methods or approximation formulas is limited because they are obtained by ignoring certain components of electromagnetic wave propagation under some approximation assumptions. Second, the relevant parameters required by these methods are either expensive to acquire or require a lot of time and effort to manually adjust.

In our previous work, we proposed a framework to automatically extract simulation parameters by using deep neural network (DNN) combined with simulation images and real SAR images [2]. In this work, we will use convolutional neural network (CNN) to directly learn the calculation formula of electromagnetic intensity from real SAR images and apply it to SAR image simulation.

The calculation formula of electromagnetic wave intensity is a function, whose input is geometric and material information, and the output is the intensity of electromagnetic wave. The basic function of DNN is to automatically learn the function from input to output through back propagation algorithm. Therefore, as long as the DNN model is trained with the correct incident and reflection information of electromagnetic wave, it may fit the calculation curve of electromagnetic wave intensity.

However, a SAR image is the result of multiple interactions between a large number of electromagnetic waves and a target. In most simulation methods, it is difficult to separate the single electromagnetic calculation from the imaging process while ensuring the whole simulation process is differentiable. To our knowledge, although there are some attempts to apply DNN to SAR image simulation [3][4], there is actually no work directly using DNN to calculate the intensity of each reflection of electromagnetic wave.

In this paper, we proposed a novel method of embedding DNN into SAR image simulation. By designing the simulation process and data structure, the function of the DNN model is equivalent to that of the original electromagnetic intensity calculation formula, and the process from electromagnetic intensity calculation to the range-azimuth imaging is completely differentiable. Thus, the DNN model can fit the calculation curve of electromagnetic wave intensity from real SAR images and be directly used in SAR image simulation.

The paper is organized as follows. Section 2 explains the method and structure of embedding DNN into SAR image simulation, including the process of the modified simulation and the design of DNN architecture. Section 3 gives the experimental data and results. Section 4 summarizes some conclusions and gives the following research contents.

2 Approach

2.1 Simulation Process

Figure 1 shows the process of the proposed SAR image simulation method which embeds the DNN model to calculate the echo intensity. This process is mainly divided into four parts: ray tracing, calculation of echo intensity

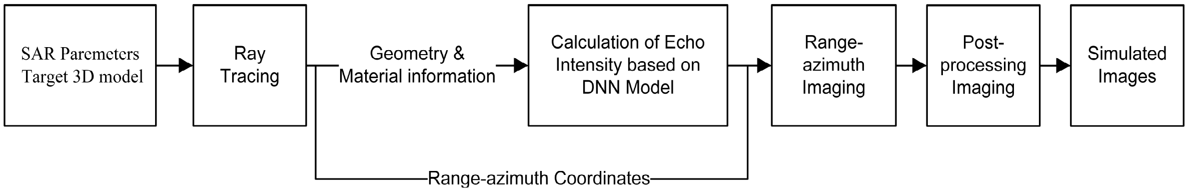


Figure 1 The process of SAR image simulation embedded with DNN model.

based on DNN model, range-azimuth imaging, and post-processing imaging.
The first part, ray tracing, compared with traditional simulation methods, needs to record not only the geometric and material information of every intersection between the ray and the surface element, but also needs to record the coordinate position of the echo in the range-azimuth image domain, so as to provide necessary information for the subsequent SAR image domain imaging.
The second part, calculation of echo intensity through DNN model, can only be input the necessary geometric and material information, but not the additional information of the imaging position. Such input and output can make DNN model consistent with the calculation formula of echo intensity in the original ray tracing method, prevent DNN model from directly calculating intensity according to position, and ensure the generalization ability of DNN model.
The third part is to image in the SAR image domain according to the position information of the echo provided in the first part and the intensity information of the echo provided in the second part. This step needs to be differentiable to ensure that the gradient information can be passed forward when training the DNN model. The computational model of this step can be regarded as a fully connected neural network model with all parameters of 0 or 1. For different images, the value of parameters will change according to the coordinates of the echo.
The fourth part, the post-processing imaging, mainly completes the change of resolution, adds the function of impact response, and image registration during DNN model training. This part can be realized by fixed convolution operation or a trainable CNN.

2.2 Ray tracing information

As shown in **Figure 1**, the information recorded during ray tracing can be divided into two categories: local geometric and material information required for calculating echo intensity, and global coordinate information required for range-azimuth imaging.
Different from the traditional ray tracing method which directly accumulates the echo intensity in the range-azimuth image domain, we need to record the information of each ray separately. Therefore, we record this information using the coordinates of the starting points of the ray in the orthogonal image field.
Figure 2 shows some of the ray tracing information, where different values are assigned different colors. The pixel value in (a) and (b) represents the range-azimuth coordinate values of the echo of the ray emitted from the pixel's position. (c) shows the material category of the local surface element when the electromagnetic wave is reflected. (d) shows the geometric information of the intersection of electromagnetic waves and surface elements.

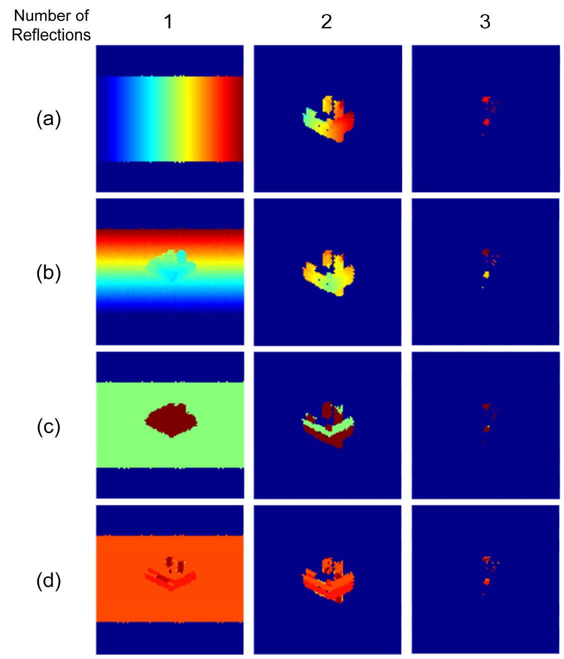


Figure 2 Some of the ray tracing information. (a) The azimuth coordinate value in the range-azimuth domain. (b) The range coordinate value in the range-azimuth domain. (c) Material category information. (d) Geometry information: The angle between the incident ray and the normal direction of the plane element.

2.3 DNN Architecture and Intensity Calculation

The DNN model for calculating the echo intensity of a single reflection can be regarded as a fully connected network, whose input is the geometric information and material information of the local surface element, and the output is the intensity in the backscatter direction and the intensity in the specular reflection direction.
The difference between the calculation of echo intensity in multiple reflections and that in single reflection is that the intensity of this reflection needs to be obtained by multiplying the intensity obtained in the last reflection by the attenuation rate obtained in this calculation. Therefore, in the network structure, it is necessary to multiply the output of the previous network and the output of the current network.
After viewing the geometric and material information obtained from ray tracing as different channels of an image, we find that the fully connected network in the direction of the image channel is completely equivalent to the full

convolutional network whose convolution kernel size is one (see **Figure 3**). Therefore, we directly use such a network structure for intensity fitting and calculation.

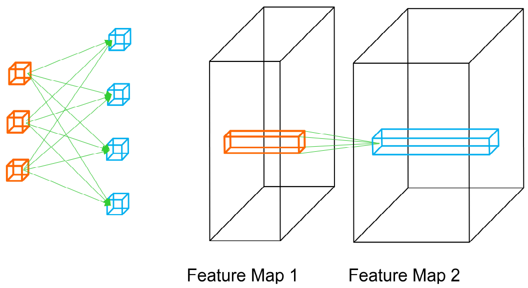


Figure 3 The basic structure of DNN model. In the image, the convolution operation with kernel size one is equivalent to the full connection operation in the channel direction.

2.4 Image formation

Since the image domain of the recorded data is different from the range-azimuth domain of the SAR image, the echo intensity calculated by the DNN model needs to be converted to obtain the simulated SAR image. In this step, the echo should be accumulated to the range-azimuth coordinates (see **Figure 2** (a)(b)) obtained by ray-tracing method. The calculation completed in this step must be differentiable in order to propagate the error value between the simulation image and the real image forward to the DNN model that calculated the echo strength in the previous step.

3 Experiment

3.1 Dataset

The real images used to train and evaluate DNN models are the images of SLICY (Sandia Laboratory Implementation of Cylinders) target in the Moving and Stationary Target Acquisition and Recognition (MSTAR) public dataset [5]. **Figure 4** shows the 3D model of SLICY target for ray tracing which was constructed from [6].

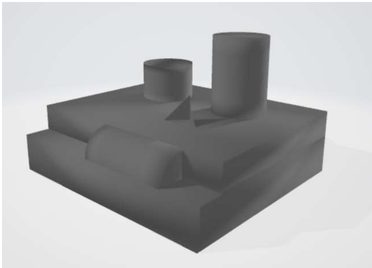


Figure 4 The 3D model of SLICY target.

In the MSTAR dataset, SLICY target has 288 images with the 30° depression angle and 274 images with the 15° depression angle. We randomly select 80% of the images under 30° depression angle and 20% of the images under 15° depression angle as the training set, and use the remaining images as the verification set.

3.2 Specific Structure

With the help of the open source deep learning framework PyTorch [7] and ray tracing engine OptiX [8], we completed the construction of the entire image simulation process and DNN model training process.

Table I and **Table II** give the specific structures of the DNN models used in this experiment. The mean square error (MSE) between the simulated image and the real image is taken as the loss function of the whole network. The optimizer is the Adam optimizer [9].

The network structure provided in this article is only to verify the methods in Section 2. In the following work, we will finish the fine tuning of the model hyperparameters to get better performance of the model.

Table I Structure of DNN Model for Calculating Echo Intensity

Layer No.	Kernel Size	Kernel Num	Mode	Activation Function
0	1×1	32	SAME	ReLU
1	1×1	32	SAME	ReLU
2	1×1	16	SAME	ReLU
3	1×1	2	SAME	None

Table II Structure of DNN Model for Post-imaging Processing

Layer No.	Kernel Size	Kernel Num	Mode	Activation Function
0	5×5	32	SAME	ReLU
1	5×5	24	SAME	ReLU
2	5×5	16	SAME	ReLU
3	5×5	16	SAME	ReLU
4	5×5	8	SAME	ReLU
5	3×3	1	SAME	Tanh

3.3 Results

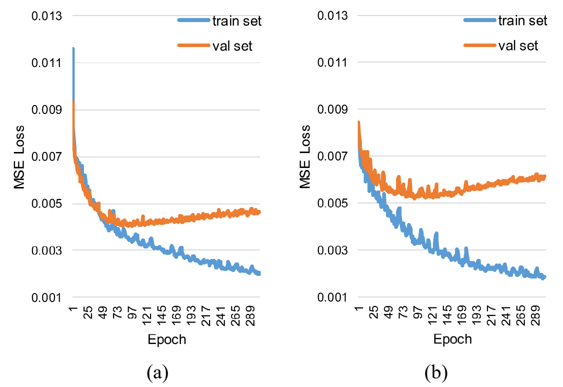
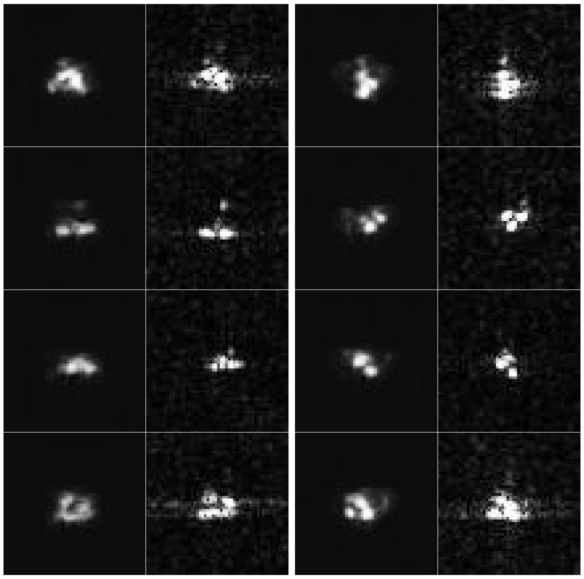


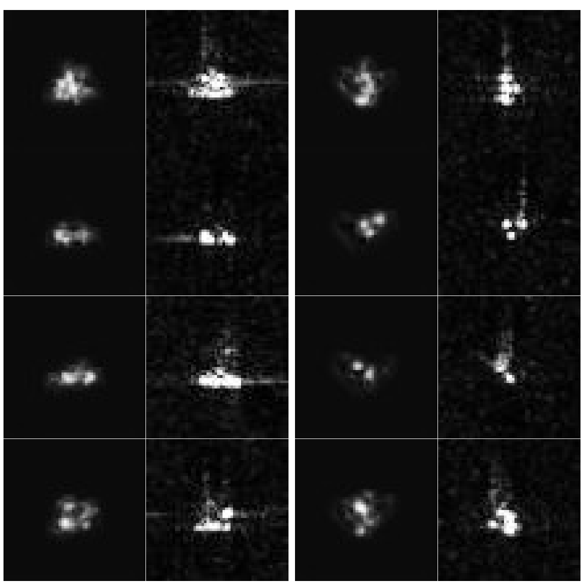
Figure 5 MSE loss value curve on the training set and verification set. (a) on the 30° depression angle data set (b) on the 15° depression angle data set

Figure 5 shows the loss value curve on the training set and verification set during the training of DNN model. **Figure 6** and **Figure 7** show the simulation images obtained by the proposed simulation method from different depression angles on the verification set. These simulation images are very similar to real SAR images in the intensity, distribution, and size of scattering points. From the loss curve, we can see that the DNN model embedded in the simulation can gradually fit the calculation method of echo intensity in the real SAR image, and in the case of less data in the 15° depression angle training set, the loss function value is still significantly reduced, which indicates that the DNN model has generalization ability.



(a) (b) (c) (d)

Figure 6 Simulation results under 30° depression angle. (a)(c) is the simulation image and the (b)(d) is the real image.



(a) (b) (c) (d)

Figure 7 Simulation results under 15° depression angle. (a)(c) is the simulation image and the (b)(d) is the real image.

4 Conclusions and Future Work

The method presented in this paper realizes the correct decomposition and combination of the original SAR image simulation, so the DNN model is directly embedded into the ray-tracing method to calculate the echo intensity. Since the steps of calculating echo intensity to image post-processing in the simulation process are differentiable, this method can directly use real SAR images to train the embedded DNN model. In other words, the embedded DNN model can directly fit the curve of calculating electromagnetic intensity in real SAR images.

In the following work, we will further adjust the architecture of DNN model, improve the calculation method of loss function, and use more kinds of target images to obtain better model generalization performance. And we will try to give the calculation curve of echo intensity fitted by the network and compare it with the physical formula or approximate formula.

5 Acknowledgement

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