Radar data simulation using deep generative networks

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Abstract: Due to the high cost of real experiments, radar data simulation plays an important role in radar applications. However, the accuracy and the calculation speed of existing simulation methods is limited by the model error and the heavy calculation of electromagnetic simulation. Here, a radar data simulation method based on deep generative network (DGN) is proposed. DGN is generative model involving deep network as the representation tool, in which the model is trained with labelled data. When the training phase is finished, the generative model can generate data samples which are similar to the real samples. The performance of the DGN is evaluated on the ground-based radar dataset, and the results show that the distribution of the generated radar data is similar to the training radar data.

1 Introduction

As the collection of radar data is difficult, expensive, and time-consuming, data simulation plays an important role in a radar system development from algorithm design to mission planning [1]. For example, in radar automatic target recognition (RATR), a large amount of training data is necessary to construct and verify the classifier. In radar system test, semi-physical simulation is a crucial step before field test [2]. According to [3, 4], existing radar data simulation can be divided into two categories: radar echo signal simulation and image simulation. The former type is based on different signal reflection models such as Kirchhoff physical optics (PO) [5], geometrical optics (GO) approximations [3], integral equation method (IEM) [6], and an approach related to the Phong shading model [7]. The later type generates radar image directly by ray-tracing [8, 9] or rasterisation methods [9]. In most real-world application, the mentioned simulators are not suitable for two reasons. First, the mentioned simulators are based on a certain physical model. However, targets are non-cooperative and some of targets may be rusty or camouflaged in most applications. It is hard to get the suitable model for these targets. Further, the simulation is based on a sophisticated electromagnetic backscattering model which requires large computation capability.

To avoid the problems of unsuitable model and large computation, building an end-to-end model that can directly generate the radar data is necessary. Recently, training an end-to-end generative model has attracted much attentions. Especially with the booming of deep network, deep generative network (DGN) has shown promising results on data synthesis from nature images to human voices. In the last few years, several DGNs have been proposed, such as deep belief networks [10], variational auto-encoder (VAE) [11], and generative adversarial networks (GAN) [12]. GAN is a widely used DGN framework. Compared with other DGNs, GAN can be trained without any Monte-Carlo approximations. Compared to VAE, GAN can be trained without introducing any deterministic bias. However, despite of its superior performance, GAN is hard to train. Great effort has been made to address this issue. For example, deep convolution generative network (DCGAN) is proposed to stable the training process by adding a set of constraints on the architectural topology [1].

The main contributions of this paper are as follows:

• The DCGAN is applied to generate one-dimensional high-resolution range profile (HRRP) for the first time, to the best of the authors’ knowledge. Compared with conventional methods that generate the radar data by building sophisticated electromagnetic models, the computational burden decreases significantly. In contrast with other DGNs, DCGAN is trained in an adversarial process and the HRRP can be generated independently without the influences of the prior information.

• In this paper, not only target HRRPs but also clutter is generated. Therefore, DCGAN can be used to simulate clutter for the study of clutter characteristics and radar data of targets under different environment.

The structure of this paper is organised as follows: The principle of GAN and its model parameters are explained in Section 2, and the proposed method is introduced in Section 3. In Section 4, two generative experiments are performed, and the experimental results are analysed. The conclusion is given in Section 5.

2 Background

2.1 Generative adversarial networks

Generative adversarial networks (GAN) is an end-to-end model which can estimate generative models via an adversarial process. GAN consists of two adversarial models: a generator $G$ and a discriminator $D$ (Fig. 1). To learn the generator's distribution $p_g$ over the generated data, input noise variables $p(z)$ is defined first. The generator is defined as a multilayer perceptron (MLP) $G(z; \theta_g)$.
Proposed method

As shown in Fig. 2, generative adversarial networks are designed composed of generator and discriminator by using DCGAN to generate HRRP. In Fig. 2, FC denotes fully connected operator, and FSC denotes fraction-stride convolution operator, and SC denotes stride convolution operator. In HRRP generator, a uniform noise distribution is taken as the input. After two fully connected operators come fraction-stride convolution operators, and the size of convolution kernel of stride convolution operator can be assigned as $1 \times N_{FSK}$, and the $N_{FSK}$ could be typically assigned to the value of 3, 5, or others. The output of HRRP generator is a fake HRRP whose length is same to the real HRRP. The HRRP discriminator consists of two stride convolution operators and two fully connected operators, and the size of convolution kernel of stride convolution operator can be assigned as $1 \times N_{FSK}$, and the $N_{FSK}$ could be typically assigned to the value of 3, 5, or others. The output of HRRP discriminator is a Boolean variable when the value of this variable is ‘real’ means the HRRP discriminator judge the input as real HRRP. The output of each operator in HRRP generator and HRRP discriminator should be through non-linear mapping, and in this paper a rectified linear unit (ReLU) activation function is selected as the non-linear mapping function.

As the generator is hard to train, the HRRP discriminator is updated in every epoch and update the HRRP generator after two epochs. The parameters of generator are saved in every epoch. When the training phase is completed, the parameters of generator which has the lowest KL distance as the best generator will be selected.

4 Experimental results

The experiments are based on measurement data of ground vehicle targets and clutter. The HRRP dataset of target and clutter dataset both consist of four different files which was collected at different time, and each file consists of 10,000 HRRP, and the number of resolution cells of each HRRP is 128. In this section, generators of target HRRP and clutter are trained separately.

4.1 Generation of targets HRRP

The original HRRP consists of both targets and clutter. For reducing the influence of clutter, we should extract the target area and then HRRP of the extracted area is treated as the input of DCGAN. The HRRP discriminator is not easy to stabilise in the training phase. The stable state of the DCGAN means that the losses of $G$ and $D$ are within a state of the DCGAN.

4.1.1 Pre-processing of targets HRRP: At first, the target area is selected by using OS-CFAR, and the average power of clutter could be calculated. To avoid the influence of clutter, we replace the HRRP out of target area with the average amplitude of clutter as shown in Fig. 3.

4.1.2 DCGAN for target HRRPs: We need to train the DCGAN using all target HRRP data. We divide the target HRRP dataset to 40 mini-batches which contain 1,000 HRRP. According to [14], the DCGAN is not easy to stabilise in the training phase. The stable state of the DCGAN means that the losses of $G$ and $D$ are within a...
certain and steady range. In our experiment, the appropriate number of training epochs for DCGAN was 10, and the batch size was 1000, which can make the training more stable. The optimiser was stochastic gradient descend the learning rate was 0.0002. After every epoch, we get the HRRP of target by using the method described in scattering centres detection and target partition and calculate the distance between the generated HRRP and the training HRRP, and the parameter of $G$ should be saved. When the training phase is over, we select the parameters with lower loss. As shown in Fig. 4 the KL distance after 40th batch is the lowest of all, and the parameters after 40th batch will be selected as parameters of generator.

As shown in Fig. 5, the generative HRRP is more and more similar to training HRRP. After epoch 0, the generative HRRP is random noise. The prototype of HRRP can be generated after epoch 2, and the outline of HRRP become more and more clear from epoch 3 to epoch 6, and the details is optimised after epoch 6. The KL distance showed in Fig. 4 reflects the same trend to subjective feeling. The KL distance descends quickly before epoch 3, and then the convergence speed become slow and the value is closer and closer to 0. The result shows that DCGAN is suitable for radar target data simulation.

4.2 Generation of clutter

When we evaluate the generated clutter, we use the all profiles of the HRRP. The generation process of clutter is same to target which is introduced in Section 4.1.1.

As shown in Figs. 6 and 7, the generated clutter becomes more and more similar to the training clutter except to the 12th batch. It became worse for that the feature of clutter is not obvious and the training process is random. The parameter in 12th batch will be selected after the training phase is over. The DCGAN is suitable for clutter as well.

5 Conclusion

In this paper, we proposed an improved DCGAN model for one-dimensional HRRP structure which can be applied to the supervised generation of HRRP database. This method is used in generating both the HRRP of targets and the HRRP of clutter. The KL distance between generated HRRP with training HRRP shows that this model can generate HRRP effectively. The DGNs are suitable for not only HRRP generation but also other radar data generations.

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