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Image Mask Constraints Based Radar Data Intelligent Generation Model

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Abstract. Aiming at the problems of limited number of electromagnetic real data and insufficient features in radar target intelligent identification, a radar data intelligent generation model based on image mask constraints is proposed to realize the effective expansion of radar Range Doppler (R-D) images. First, a set of radar 1-D echo data of non-cooperative ship targets under real sea conditions is acquired. The velocity information is well preserved by using Fourier transform in the signal preprocessing stage, and the interactive program is designed to perform image annotation to form an image dataset. Then, a GAN-based data generation network model is built to take the image dataset as input, and a multi-scale constraint based on generalized regularization technique is designed to improve the similarity between the generated image and the real image to solve the problem of insufficient samples. Finally, an image mask is introduced into the generator to specify the generation location of target, and at the same time to improve the sample diversity during the data generation process. The dataset generated by the proposed method takes into account the similarity and diversity, and can provide data guarantee for the subsequent high-precision recognition of radar signals under small sample conditions.

Keywords: Generative Adversarial Networks, Radar Data Augmentation, Deep Learning.

1. Introduction

Radar data augmentation technology provides data support for radar target recognition technology, which is crucial for achieving accurate tracking and situational awareness. When the pulse repetition frequency of the radar is low or the target is an advanced non-cooperative target, it is usually difficult to obtain sufficient training data, which causes difficulties in the training of target recognition models. Since the small sample training set cannot fully reflect the target characteristics, the data set needs to be expanded by generating new samples, and radar image augmentation technology is an effective technique to solve this problem. Image augmentation technology refers to the use of limited data samples to generate incremental data, the commonly used methods can be divided into two categories, namely, the traditional method based on simulation and the generation method based on convolutional neural network. The traditional data simulation method is an iterative process, by abstracting a model for a certain level of the characteristics of the real system, and then set the input conditions for the test, according to the test results and validation of the situation and constantly modify the model and parameters, until it meets the purpose of a certain level of the simulation of the system. Goodfellow et al [1] proposed a generative adversarial network model (GAN) framework in 2014, which aims to generate new data samples by learning the distribution of real data. The model introduces an adversarial mechanism to continuously optimize the generative model in order to generate data that is closer to the real one. Subsequently, Mirza et al [2] proposed Conditional Generative Adversarial Networks (CGAN), which added supervisory conditions to the original GAN to make the generated images more in line with the specified requirements. Chen et al [3] proposed information maximizing generative adversarial nets (Info GAN), which learns hidden variable representations by mutual information maximization and decouples features in a completely unsupervised way.

With the development of GAN, researchers gradually applied the technology on the field of radar image generation to improve the quality of radar images and enhance the target recognition capabilities. Yin Xiang et al [4] used GAN to generate samples with similar feature distribution,

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thus extending the target dataset and narrowing the quantitative gap between the target samples and the sea clutter samples. BU K et al [5] proposed an adversarial migration learning architecture for signal recognition based on GAN, which combines adversarial training and knowledge migration to generate samples approximating the real data. Li Hui et al [6] realized the augmentation of radar signals under small sample conditions through cycle-consistent generative adversarial network (Cycle GAN)[7], effectively suppressing the cross terms while generating time-frequency maps of noise attenuated signals, and presenting the time-frequency characteristics of the radar signals more accurately. TANG B et al [8] used an auxiliary classifier generative adversarial network (ACGAN) to realize data enhancement, which alleviates the problems of overfitting, generator non-convergence and pattern collapse of traditional GAN. Zhu et al [9] proposed a weighted assisted generation adversarial network, based on the supervised learning of labeled samples to automatically select high-quality samples for generation, which effectively improves the performance and stability of the recognition of radar targets with small samples. Wang Jiao et al [10] proposed a conditional generative adversarial network introducing self-supervision mechanism, combining the advantages of ACGAN and Fast-GAN [11], and using cross-layer excitation pattern generator to improve the image resolution.

In this paper, an intelligent radar data generation model based on image mask constraints is proposed. The proposed model includes a generation module and a discrimination module, which improve each other's performance through adversarial training. In addition, a masked image is introduced to guide the model to generate ship targets at specified positions, and a loss function is designed to promote the convergence of the model to a local optimal solution. This method generates radar R-D images with ship targets, which can solve the problem of data scarcity.

2. Methodology

2.1 Data generation model based on masked image

2.1.1 Overview of the proposed method

As shown in Fig. 1, the proposed deep convolutional neural network model for generating R-D images integrates CGAN and adversarial optimization techniques. The mask technique is utilized to guide the generator to generate location-specific ship targets. This method shows great technical advantages in the field of R-D data generation.

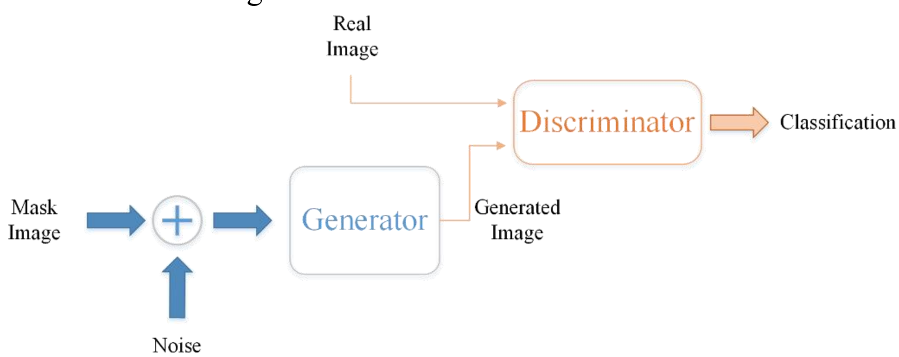

Fig. 1 Modeling framework for the proposed method.

2.1.2 Composition modules

The generator module uses a multilayer coded feature extraction structure designed to extract given positional and boundary features from the input mask image, and then use these features in combination with random noise to generate an entirely new image. The feature extraction layer uses the deconvolution layer to expand the feature map, followed by the pooling layer to refine the feature space, the batch normalization layer to maintain the stability of the training process, and the ReLU activation function to introduce nonlinear factors, which together promote the model's

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learning from low-dimensional features to high-dimensional features. With the layer-by-layer depth of the coded feature extraction structure, the model is not only able to capture low-level visual elements such as color, texture, shape, etc., but also gradually refine the deeper meanings and abstract information of the image, realizing the image generation from pixel level to image level.

Mask image a binary image with highlighted areas representing the target location and dark areas representing the background or irrelevant areas. The mask image is introduced at the input layer of the generator network to control the features, and the mask is fused with the random noise input by element-wise addition. During the image generation process, the image mask is used as conditional information to guide the GAN generation process. To ensure that the mask image can effectively guide the target location, special loss function is designed to give highlighted regions higher weights. The above design enables the generator to refer to the mask information when generating an image and accurately place the target at the specified location.

The task of the discriminator module is to determine the authenticity of the image produced by the generator. The first five layers of the feature encoding and extraction process use an efficient combination of patterns: first, a Conv2D convolutional layer captures the local details of the image, then a pooling layer reduces the data dimensions and preserves the key features; next, a batch normalization layer ensures the stability of the training process; and lastly, a Leaky ReLU activation function introduces the nonlinearities, and a Dropout layer prevents overfitting. In addition, the sixth layer is the key layer for feature integration and decision output. First, the Conv2D convolutional layer is used for further feature extraction. Then, the flattening layer converts these 2D feature maps into 1D vectors for subsequent processing. Finally, the fully-connected layer integrates these 1D features and outputs a probability value between 0 and 1 via the Sigmoid activation function.

2.1.3 Loss functions

GAN is a deep learning model that achieves high quality image generation through adversarial training between generator and discriminator. During the training process, the generator tries to trick the discriminator into confusing the generated image with the real image, while the discriminator tries to categorize correctly. The objective function can be expressed as:

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x|y)] + E_{z\sim p_z(z)}[\log(1-D(G(z|y)))] \quad (1)$$

Among them, x is the real image, y is the fault label, z is the random noise, the label of the real image is 1, and the label of the generated image is 0.

Assuming there are N real samples and N generated samples. The discriminator needs to classify the generated image and the real image. The loss function is denoted as:

$$L_D = -\frac{1}{2}\left(\sum_{i=1}^{N} log\left(D\left(x^{(i)}\right)\right) + \sum_{i=1}^{N} log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right)\right) \quad (2)$$

Assuming that the output image size of the generator is $\mathrm{H} \times \mathrm{W} \times \mathrm{C}$ (height, width, and number of color channels), the real image and the mask image are also of the same size. The generator learns to map random noise onto the generated image, reducing the data distribution difference between the generated image and the real image. The loss function is expressed as:

$$L_G = \frac{1}{HWC}\sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C} \alpha[h,w,c]\cdot(G(z)[h,w,c] - x[h,w,c])^2 \quad (3)$$

Among them, α is the weight factor, z is the noise, $\mathrm{G(z)}$ is the generated image, x is the real image, $[h,\mathrm{w},\mathrm{c}]$ is the pixel position, and HWC is the total number of pixels.

The weight factor α is introduced to consider the mask information during the training process, evaluating the consistency of the generated image with the specified position in the image mask. The weight value of the highlighted area in the image mask is larger, thus guiding the target to be generated at the specified location.

In summary, the technical route of using mask image to specify the target position in the generated image can be effectively realized by introducing a mask input layer, designing a suitable fusion mechanism and adjusting the loss function in GAN. This method not only improves the

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accuracy and controllability of the generated image, but also provides a new way for the application of GAN in complex image generation tasks.

2.2 Mosel Training Process and Test Results

2.2.1 Training dataset preperation

The experimental site is located in the coastal area of Yantai City, Shandong Province, and mainly collects sea clutter data and marine vessel target data under different sea conditions. During the experimental period, the radar is installed in the Yantai First Beach test site, and mainly adopts the antenna gaze observation mode. Under different sea conditions and environments, the radar antenna gaze direction was adjusted to gaze at the anchored ships or navigation buoys on the sea surface, and the radar gaze pattern data ranging from a few seconds to a few minutes were collected [14]. The distance Doppler images of the collected vessel data are shown in Fig. 2.

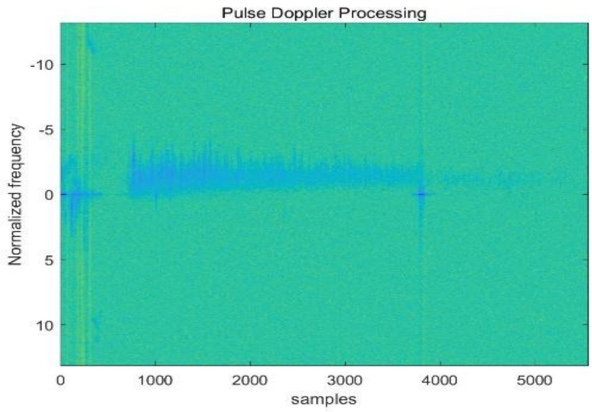

Fig. 2 Ship data collected at sea state level 2.

In the data processing process, data cleaning is first performed to filter and remove the repetitive and redundant parts of the data. Then, a self-developed human-computer interaction annotation program is utilized to annotate ship targets and clutter distribution ranges on the image dataset. Next, the ship target is captured randomly by taking the ship coordinates as a point in the image and capturing the image of specified size within the neighborhood. Data processing methods such as rotation and folding are used to realize data transformation. Finally, the data is normalized to balance the contribution of various features, improving the stability and accuracy of the machine learning algorithm.

2.2.2 Generating results

Based on the above process, a generative artificial intelligence model was trained, and the results are shown in Fig. 3.

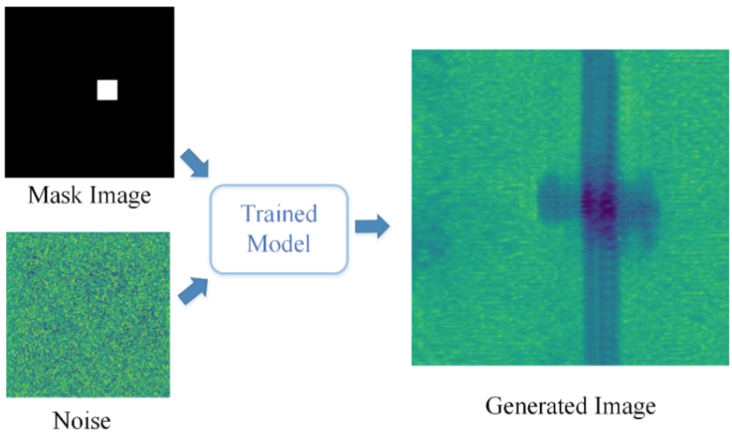

Fig. 3 Image generation. The image mask and random noise are fed into the trained model to generate the radar R-D image.

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It can be seen that the simulation result of the generated data is good, with clear and accurate representation of target features. The location of the generated target is consistent with the specified location in the mask image, which meets the requirements of on-demand generation. The imaging resolution of the generated images is high, and the edges of the target and background are clear. It is worth mentioning that the generated data not only improves the simulation performance, but also enhances the diversity characteristics, reflecting the unique advantages of generative artificial intelligence in data enhancement.

3. Summary

In this paper, we propose an intelligent generation model for radar data based on image mask constraints. First, the model can autonomously generate highly realistic ship target images through continuous adversarial learning between the generator and the discriminator. This not only greatly improves the efficiency of data generation, but also ensures the richness and quality of the data. Second, based on the powerful generation capability, combined with the shape constraints provided by the image mask, the location of the generated target can be specified. The feature diversity of the generated image is improved, which can effectively enhance the noise immunity and generalization ability of the subsequent ship target detection and recognition model. In addition, compared with other data generation methods, the model does not require tedious manual parameter adjustment and scene modeling, which greatly reduces the cost and time consumption of the data preparation stage, and is characterized by high automation and intelligence.

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