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Target Representation and Classification with Limited Data in Synthetic Aperture Radar Images

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Abstract

Recently, with the introduction and development of deep learning based detection and classification methods, various applications in optical images have been put into practice. However, few automatic target recognition (ATR) approaches in Synthetic Aperture Radar (SAR) images can be used practically. Two reasons underlying it are the complicated imaging mechanism of SAR and limited sample data for optimizing the models. This paper focus on target representation and classification with limited data based on zero-shot learning (ZSL) and few-shot learning (FSL), and provides a comprehensive investigation of existing ZSL/FSL algorithms.

1 Introduction

Due to the imaging mechanism of Synthetic Aperture Radar (SAR), features in images of the same target under different observation angle, such as distributions of strong scattering points, vary a lot from each other. Besides, it's difficult or even impossible to acquire SAR images for non-cooperation targets. The two reasons above limited the number of available training samples, which will result in over-fitting problem. Learning from no or only a few samples is known as Zero-shot Learning (ZSL) [1-3] or Few-shot Learning (FSL) [5].

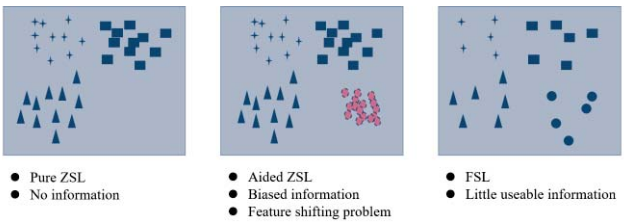

Figure 1. Illustration of three types of ZSL or FSL problems: PZSL (left), AZSL (middle), and FSL (right) .

This paper investigated existing Zero-shot or Few-shot learning techniques for targets classification in SAR images. Three types of learning problems are concerned, i.e. pure ZSL (PZSL), ZSL aided by other source of data (AZSL), and FSL, as shown in Figure 1. In PZSL, there is no useable information for the zero-shot target. However, although it is of great potential use in the field of target recognition in SAR images, it has been barely studied. Song and Xu proposed to build a feature space based on deep neural networks (DNN) using images of known targets [1]. The zero-shot target can be recognized via comparing the distance between zero-shot and known targets in this feature space. Since the feature space is learned from the known targets, the distribution of zero-shot target images isn't compact enough to be discriminated correctly.

In other research, other sources of data of zero-shot target, such as optical images [2] or simulated SAR images [3], are used as replacements of real data. In this case, however, the information concerning the zero-shot target is biased, which we called feature shifting problem. In [2], the authors proposed to learning an association rule for SAR and optical images, thus the zero-shot SAR images are classified in terms of the associated optical images. [3] addressed the feature shifting problem in simulated SAR images firstly by non-essential factor suppression step, and introduced averaged margin index (AMI) for selecting optimal classifier.

As illustrated in Figure 1, in FSL, the distribution of each target is sparse due to the limited number of samples. Transfer learning and generative model are two main means that used to improve the generalization ability of the model [4-6]. Transfer learning methods use the classifier that trained on other datasets as a basis, and fine-tune the parameters on few-shot samples. Generative methods such as generative adversarial nets (GAN), is used to generate new samples, thus make the distribution less sparse.

The next three sections of the remainder of the paper recall the existing methods addressing PZSL, AZSL and FSL problem respectively.

2 PZSL

Based on the cluster assumption, there exist a feature space where samples of the same target clustered together. Generally, target classification can be formulated as a feature extractor which projected the original data into the feature space, followed by a simple classifier which evaluates the similarity/distance between any two extracted features in the space. The extracted feature is also known as the representation of the original data. Since no samples of zero-shot target is available, feature space learning is crucial.

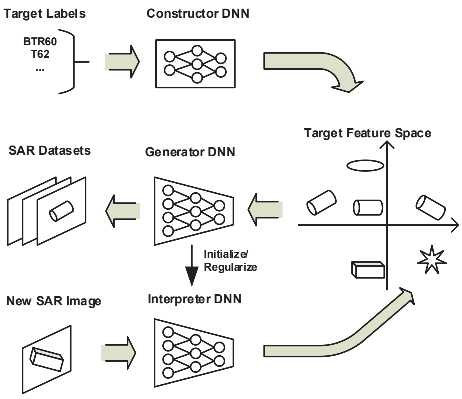

Figure 2. Generative DNN-based SAR target feature space construction for PZSL.

As illustrated in Figure 2, DNN can learn a faithful representation as well as construct a continuous feature space automatically [1]. It consists of three subnetworks: the constructor and the generator DNNs generate SAR images given the labels and the orientation angles, and the output of the constructor or the input of the generator is the learned representation of the input; the interpreter DNN maps real SAR images of known targets to the learned feature space. By optimize the following two objective functions, the networks learn the relationships of SAR images and the representations,

$$\begin{aligned}&\min_{\theta_c,\theta_g} L\big(G\big(C(\mathbf{c};\theta_c),\mathbf{v};\theta_g\big)||\mathrm{X}\big)\\&\min L\big(p(\mathbf{F}|\mathbf{c})||p(\mathbf{F}|\mathrm{X}_{x\sim D})\big)\end{aligned} \tag{1}$$

Experiments results in [1] show that the representations of known targets such as T62, D7 and ZSU234 in feature space are well separated and centered around the clusters. Though the distribution of zero-shot target is more dispersive which makes it difficult for practical classification of zero-shot targets, the interpreter DNN is able to accurately reflect the similarity/dissimilarity of a new unseen target to known targets.

3 AZSL

It is straightforward to use other sources of data to assist zero-shot learning, since the underlying semantic maps of them are the same. Optical and simulated images are two main auxiliary sources of data that used in SAR automatic target recognition. Due to the different imaging mechanisms between optical and SAR images, and the limitation of the simulation algorithms, the features extracted from these two sources may be greatly different from that from SAR images. Two AZSL methods are proposed for addressing the feature shifting problem.

3.1 Domain Transfer

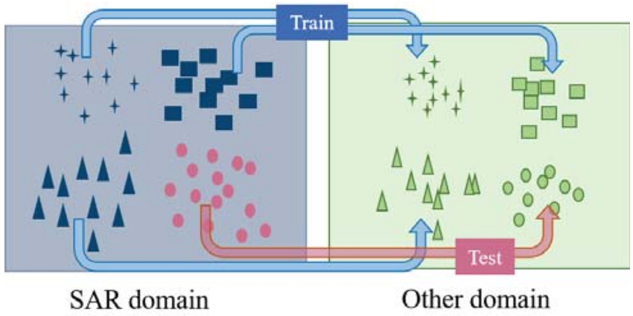

Figure 3. Illustration of domain transfer for AZSL.

Let S^K and S^{ZS} be the SAR images of known targets and zero-shot targets, and T^K and T^{ZS} the respective other source of data. AZSL is to predict the labels of S^{ZS} given S^K, T^K and T^{ZS}. Domain transfer learns a projection rule from S^K to T^K, so that $T^K \approx f(S^K;\boldsymbol{\theta})$. By comparing the similarity/distance between $f(S^{ZS};\boldsymbol{\theta})$ and T^K, T^{ZS}, zero-shot targets can be classified. Different from PZSL, since the samples of zero-shot targets in other domain are available, the parameters $\boldsymbol{\theta}$ in transferring rule can be restricted by T^{ZS} by optimizing Equation 2.

$$\begin{aligned}&\min\left\|f(S_i;\boldsymbol{\theta})-T_j\right\|_2 \quad when\ y_i^S = y_j^T\\&\max\left\|f(S_i;\boldsymbol{\theta})-T_j\right\|_2 \quad when\ y_i^S \neq y_j^T\end{aligned} \tag{2}$$

Where the y_i^S and y_j^T denote the label of ith SAR images and other source data.

Instead of directly map the SAR images to optical images, Toizumi et al proposed to transfer both sources of data into a shared low-dimensional space, and learn projection rules for SAR and optical images respectively [2]. It is worth noted that, however, domain transfer assumes that all types of targets share the same transferring rules.

3.2 Max-tolerability Principle

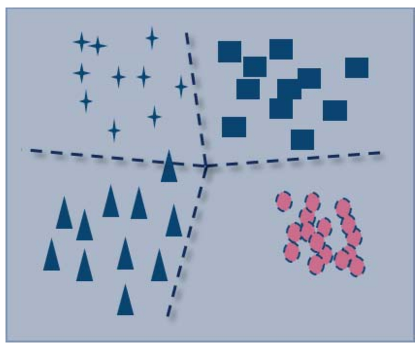

Figure 4. Illustration of max-tolerability principle for AZSL. The red circles represent simulated SAR images of zero-shot targets. The dotted lines denote the imaginary classification hypersplanes.

Simulation is a convenient and cheap way to generate SAR images [7]. However, although the profile of shadow and target in simulated image is similar with that in real SAR images, the simulated samples distributed more compact than real images in feature space.

When using simulated data as training images directly, Max-tolerability principle requires that on the premise of high classification accuracy of known targets, classifier should reserve as large as possible classification space for zero-shot target. As illustrated in Figure 4, the dotted lines represent the classification hyperplanes. Based on the max-tolerability principle, the hyperplanes should be closer to the known targets instead of zero-shot targets (red circles).

In [3], Song et al proposed averaged margin index (AMI) for probing the classification hyperplanes, which is defined as

$$AMI_T = \frac{1}{M}\sum_{i=1}^{M} MI_{T-T_i} \tag{3}$$

Where M is the number of types of known targets. MI is margin index, and is determined by the classifier and the synthetic feature,

$$I_{syn} = (1-\alpha)\overline{f(A)} + \alpha\overline{f(B)} \tag{4}$$

where $\overline{f(A)} = \frac{1}{N}\sum_{i=1}^{N} f\left(I_A^i\right)$ is averaged feature of target A, and $\alpha \in [0,1]$ is synthetic weight. It can be inferred that as α grows, the predicted label changes from A to B. Margin index is defined by the value of α when this changes happened. However, poor simulated images will decrease the classification accuracy of zero-shot targets.

4 FSL

In recent years, research of relieving the need of training samples has arisen great attention. Among the proposed approaches, transfer learning and generative model are two popular and useful methods.

4.1 Transfer Learning

Transfer learning [8] uses the target datasets (such as MSTAR) to train the model that has trained on source datasets at first (VGG16, ResNet, etc.), as shown in Figure 5. The original network M_S is trained the source datasets S. Note that S can be either SAR images [4] or simulated images [11] [12], optical images, hyper-spectral images and so on. Then partial trained parameters θ_s is used in the target network M_T, and the left parameters of M_T is trained on target samples T_r. In avoiding to train the whole network from a scratch, transfer learning can decrease the risk of over-fitting effectively.

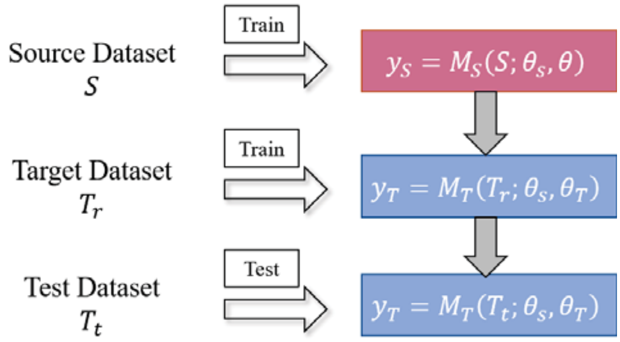

Figure 5. Framework of transfer learning.

4.2 Generative Model

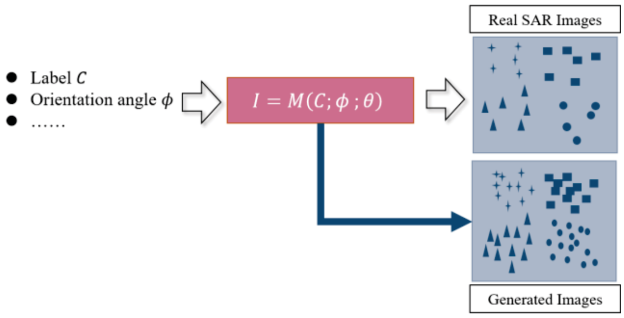

Figure 6. Generative networks learn to genete SAR images using limited training samples.

The main purpose of generative models is to compensate the lost information, so that the distribution of training samples is closer to that of test samples [5] [6].

As shown in Figure 6, generally generative models take the label, orientation angle and other parameters of SAR images as input, and predict the corresponding image. After trained the model, it can be used to generate the images at other observations. Generative adversarial nets (GAN) [9] [10] which are known for its high-fidelity image generation ability, are most used [5]. However, due to the limited number of training samples, the generated test images fail to reveal the intrinsic features of real SAR targets when the interval angles between training and test images become larger.

5 References

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