LAYER-WISE REPRESENTATIVE EXEMPLAR SELECTION-BASED INCREMENTAL LEARNING FOR SAR TARGET RECOGNITION

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ABSTRACT

Over the past few years, the flourishing of deep learning has strongly promoted synthetic aperture radar (SAR) automatic target recognition (ATR) advancement. Many SAR ATR methods have performed well under static environment assumptions, but in real application scenarios where target categories continue to increase over time, they are prone to catastrophic forgetting on old categories of targets. In response to this problem, this paper proposes a novel method named layer-wise representative exemplar selection-based incremental learning (LwRSIL) for SAR target recognition. Specifically, we propose a layer-wise representative exemplar selection strategy, which is capable of picking out representative exemplars covering the entire class distribution. To achieve incremental learning of the ATR model, a multi-task mixed loss is formulated to continually learn reasoning capability on new categories while recalling the knowledge of old categories. Experiments on the moving and stationary target acquisition and recognition (MSTAR) dataset demonstrate that the proposed method is competitive with some state-of-the-art incremental ATR methods.

Index Terms— Synthetic aperture radar, incremental learning, exemplar selection

1. INTRODUCTION

Synthetic aperture radar (SAR) has found wide applications in both military and civilian domains due to its high resolution in all-day and all-weather conditions. However, its unique imaging mechanism poses a critical challenge to understand the rich information of SAR images. Therefore, automatic target recognition (ATR) plays a crucial role in intelligent SAR image interpretation tasks.

With the advancement of deep learning, an increasing number of SAR ATR methods based on this technology have been proposed in the past few years. To name just a few, Chen *et al.* [1] presented a fully convolutional network to automatically achieve SAR target classification. Ren *et al.* [2] devised an extended capsule network for SAR ATR tasks under complex scenarios. In [3], a multi-view deep learning framework was proposed to capture discriminative features for SAR target recognition.

Nevertheless, traditional SAR ATR methods are developed for static scenarios, which assumes a fixed target category library. In real-world applications, the target categories will continuously expand over time. To endow the ATR model with the ability to be updated and learn information from targets of new classes, some replay-based incremental learning [4] methods have been proposed. Dang *et al.* [5] presented a class boundary exemplar selection algorithm to achieve incremental SAR target recognition. Yu *et al.* [6] devised a multilevel knowledge distillation strategy for incremental SAR ATR tasks. Tang *et al.* [7] proposed an error correction incremental learning method to realize target recognition for SAR targets. Although these replay-based methods demonstrated effectiveness in incremental SAR target recognition to some extent, the selected replay exemplars can be insufficiently representative of targets from old classes.

To address this challenge above, we propose a layer-wise representative exemplar selection-based incremental learning (LwRSIL) method for SAR target recognition. Specially, a layer-wise exemplar selection strategy based on the class-hierarchical distribution is designed, which selects representative exemplars covering the entire class distribution. To achieve incremental learning, we devise a multi-task mixed loss to update the ATR model from information of new classes while recalling the knowledge of old classes. Experiments on the MSTAR dataset demonstrate that our proposed method is superior to some advanced incremental learning methods for SAR ATR tasks.

2. PROPOSED METHOD

The overall flowchart of the proposed method is depicted in Fig. 1, in which exemplar selection and incremental learning are two vital steps for incremental SAR target recognition. In

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what follows, the proposed method is described in detail.

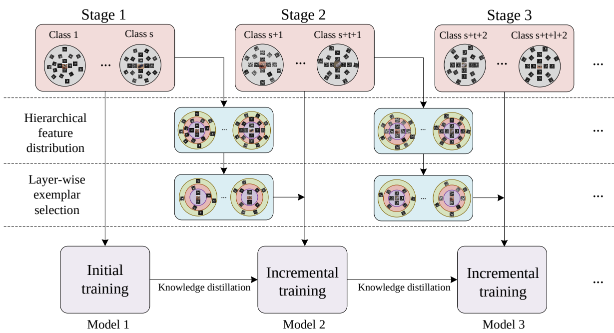

Fig. 1. The flowchart of proposed LwRSIL.

2.1. Exemplar Selection

In order to alleviate catastrophic forgetting about the knowledge of old categories of targets, It is feasible and meaningful to select and store a small set of representative examples from old categories of targets covering the entire class distribution. Nowadays, the widely popular exemplar selection methods can be grouped into two streams: the herding-based and random-based. Among them, the herding-based method can pick out those samples surrounding the class prototype, lacking coverage of the entire class distribution. The quality of the samples selected by the random-based method is uncertain, so it is difficult to characterize the entire class distribution stably. In view of this, a layer-wise representative exemplar selection strategy is proposed for incremental SAR target recognition task. Let $\mathbf{X}_y = \{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n\}$ be a sample set belonging to class y. Assume that $\mathbf{F}_y = \{\mathbf{f}_1, \mathbf{f}_2, \cdots, \mathbf{f}_n\}$ represents the dimensional embedding feature corresponding to the sample set $\mathbf{X}$. The proposed layer-wise representative exemplar selection is summarized as the following three steps. For ease of understanding, features of samples are projected into two-dimensional space, as shown in Fig. 2.

1) Class distribution layering: First, the prototype of the class y from sample set $\mathbf{X}$ is calculated according to the following formula:

$$\mathbf{P}_y = \frac{1}{n}\sum^{n}\mathbf{f}_i, \tag{1}$$

Then, the farthest distance D^i_{max} from all samples to the prototype is calculated as follows:

$$D_{\max} = max\{\|\mathbf{f}_i - \mathbf{P}_y\|_2, i = 1, \ldots, n\} \tag{2}$$

Afterwards, m concentric circles are drawn with $\mathbf{P}_y$ as the center and R_j as the radius.

$$R_j = \frac{j}{m} \cdot D_{\max}, j = 1, \ldots, m \tag{3}$$

where the maximum value of m is the number of samples selected for each category of target.

Next, to ensure the diversity of the selected exemplars, the difference between layers should be initially guaranteed. To this end, the density of each layer can be computed according to the following formula:

$$\rho_j = \frac{N_j}{S_j}, j = 1, ..., m \tag{4}$$

where N_j is the number of samples contained in this layer, S_j refers to the area of this layer.

Finally, we calculate the variance of all density ρ_j ($j = 1, \cdots, m$) in each iteration, and hierarchize the class distribution by selecting the one with the largest variance in all iterations. The calculation processing is as follows:

$$\sigma_j^2 = \mathrm{variance}(\rho_1, \rho_2, ..., \rho_m) \tag{5}$$

$$\delta^2 = append(\sigma_j^2) \tag{6}$$

$$s = index(\arg\max(\delta^2)) \tag{7}$$

where $variance$ denotes the variance of the calculation, σ_j^2 represents the variance in the j-th iteration, δ^2 is a list that records the variance generated in each iteration, and $index$ indicates the operation to obtain the index.

2) Exemplar confirmation within layer: After the entire class distribution is layered, it is necessary to determine the number of samples selected for each layer. Considering the fact that high-density areas contain more information about targets, this paper follows the criterion that more exemplars should be selected in high-density areas. Specially, first we randomly initialize a exemplar $\mathbf{x}_{init}$ within each layer (as depicted in green exemplar in Fig. 3). Then, the number of exemplars to be selected in each layer can be determined based on its proportion to the total number of samples. Mathematically, the number of exemplars selected in the each layer are determined according to the following formula:

$$n_j = rounding(\frac{M^{\cdot}(N_j - 1)}{N - s}), j = 1, 2, ..., s \tag{8}$$

where n_j is the number of samples to be selected in the j-th layer, $rounding$ denotes rounding operation, M is the total number of samples to be selected, N_j is the total number of samples in the this layer, N is the total of samples for this target, and s is the number of samples initialized.

3) Diverse exemplar selection: In order to ensure that the exemplars selected are as diverse as possible, the exemplars selected within each layer should be as spread out as possible so that they are more evenly distributed in space and the differences between them are greater. So we use the principle of uniform sampling within the layer to select the exemplars. We first calculate the distance from each sample in the layer to the initialized exemplar. Then, we calculate the maximum distance d_{max}, divide it into $n_j - 1$ equal parts, and select the exemplar closest to each equidistant point.

$$d_{max} = max\{\|f_{x_n} - f_{x_{init}}\|_2, n = 1, 2, ..., N_j\} \tag{9}$$

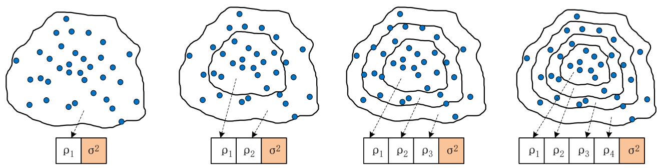

Fig. 2. The diagram of hierarchical feature distribution.

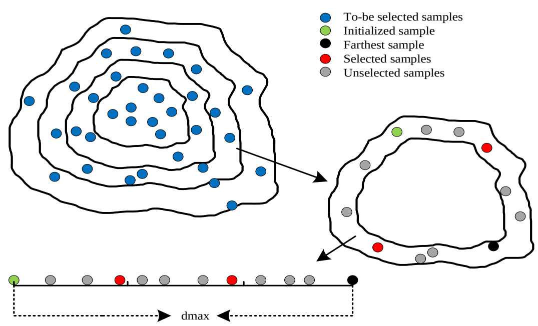

Fig. 3. The diagram of in-layer crucial exemplars selection.

$$l_m = \frac{d_{\max}}{n_j - 1} \cdot m, m = 1 \ldots n_j \tag{10}$$

$$x_m = argmin\{|\|f_{x_n} - f_{x_{init}}\|_2 - l_m|, m = 1, 2, ..., n_j\} \tag{11}$$

where l_m represents the distance from the m-th partition point to the initialized sample, $|\|f_{x_n} - f_{x_{init}}\|_2 - l_m|$ is the distance from the samples within this layer to the j-th partition point, and x_m is the selected sample (red, green, and black samples in Fig. 3).

2.2. Multi-task mixed loss

After picking out the exemplars from old categories of targets, how to continually update the ATR model with those saved exemplars from old categories and samples from new categories is another key problem for incremental SAR target recognition tasks. In this paper, a multi-task mixed loss is proposed to continuously generalize on new categories of targets while preserving the reasoning ability on old categories of targets.

Initially, we use cross-entropy loss to learn features from all new and old class data, formulated as follows:

$$L_{cls} = -\sum_{i=1}^{C}\sum_{j=1}^{N} Y_{x_j,i} \log\left(p\left(y = i \,|x_j\right)\right) \tag{12}$$

where N is the number of samples for i-th category of target, $Y_{x_j,i} = 1$ if the samples x_j belongs to i-th category, otherwise, $Y_{x_j,i} = 0, p(y = i|x_j)$ denotes the predicted probability that the classifier gives the sample x_j belonging to category i.

Furthermore, we employ soft labels generated by the old model, which exhibit a smoother distribution compared to hard labels, as the target for distillation, formulated as follows:

$$L_d = -\sum_{k=1}^{s}\sum_{x \in X_{old}} q_k(x) \log p_k(x) \tag{13}$$

$$q_k(x) = \frac{e^{\hat{o}_k(\mathbf{x})/T}}{\sum_{m=1}^{s} e^{\hat{o}_m(x)/T}}, p_k(x) = \frac{e^{o_k(x)/T}}{\sum_{m=1}^{s} e^{o_m(x)/T}} \tag{14}$$

where, $\hat{o}$ and o represent the soft labels generated by the model in two consecutive stages, T is the temperature parameter, and s is the number of old classes.

Above all, the total loss for optimizing the whole model in our method can be calculated as:

$$L_{all} = L_{cls} + \alpha L_d \tag{15}$$

where α is the weight that balance the importance of two losses.

3. EXPERIMENTAL RESULTS

To assess the efficacy of the proposed method, this paper conducts a series of experiments on the MSTAR benchmark dataset. All SAR images in the MSTAR dataset were captured by the U.S. Sandia National Laboratory using a 10-GHz X-band spotlight SAR sensor. The resolution of each SAR image is 0.3m $\times$ 0.3m. To minimize redundant background information, all images were cropped to a 64 $\times$ 64 pixel region of interest. In this paper, we divided the MSTAR dataset into two sets: the initial class set and the incremental class set. The initial class set consists of four classes, namely: ZSU23/4, D7, BRDM2, and BTR70. The incremental class set includes T72, BMP2, 2S1, Z1L131, T62, and BTR60.

The hyper parameter α is set to 0.5, SGD optimizer is adopted for optimizing the proposed model with a learning rate of 0.01. The number of preserved exemplars for each old class is set to 30, and one new class is added in each incremental stage.

In the exemplar selection comparison experiment, Herding [8], CBesil [5], and Random [9] are employed as competitors. Meanwhile, JT (Joint Training) [10], incremental classifier and representation learning(iCaRL) [8] , class boundary exemplar selection based incremental learning(CBesil) [5], incremental class anchor clustering(ICAC) [10] , and error correction incremental learning(ECil) [7] are utilized as holistic incremental learning comparison methods.

3.1. Performance evaluation with different exemplar selection methods

In this section, we experimentally validate the superiority of our proposed exemplar selection method over other exemplar selection methods in the SAR incremental target recognition task. The experimental results are presented in Table 1. It can be seen from Table 1 that our method outperforms other exemplar selection methods in terms of recognition performance at each incremental stage. This superiority can be attributed to our layer-wise representative exemplar selection approach, which carefully chooses more diverse and discriminative exemplars to better effectively preserve information from the original dataset.

Table 1. The recognition rate(%) in each incremental stage of all exemplar selection methods on MSTAR dataset.

Method	number of classes						
	4	5	6	7	8	9	10
Herding [8]	99.29	96.70	96.23	94.41	93.03	87.95	88.04
CBesil [5]	99.29	87.33	81.32	82.63	78.22	74.59	75.87
Random [9]	99.29	96.36	95.31	94.83	93.69	92.30	90.87
Ours	**99.29**	**98.64**	**98.15**	**97.59**	**95.33**	**92.70**	**91.62**

3.2. Performance evaluation of different incremental learning methods

In this section, we design experiments to validate the superiority of our proposed method compared to other incremental learning approaches. The experimental results are presented in Table 2. As shown in Table 2, our method outperforms other approaches in recognition performance at each stage, and the performance gap with the JT method is also smallest. This is mainly because the exemplar selection method and multi-task loss function employed by our method can better preserve the model's recognition performance for the old classes

Table 2. The recognition rate(%) in each incremental stage of all incremental learning methods on MSTAR dataset.

Method	number of classes						
	4	5	6	7	8	9	10
JT	99.29	99.15	98.21	98.79	98.51	98.23	97.87
iCaRL [8]	99.29	96.70	96.23	94.41	93.03	87.95	88.04
CBesil [5]	99.29	87.33	81.32	82.63	78.22	74.59	75.87
ECil [7]	99.29	97.46	96.87	94.11	94.00	88.22	90.04
ICAC [10]	99.29	95.96	88.14	86.57	84.05	83.63	81.77
Ours	**99.29**	**98.64**	**98.15**	**97.59**	**95.33**	**92.70**	**91.62**

4. CONCLUSION

This paper proposes a novel exemplar selection-based incremental learning method for SAR target recognition. The contributions of this paper can be summarized as two aspects. First, a layer-wise exemplar selection strategy which can cover the entire class distribution is proposed to alleviate the problem of catastrophic forgetting for incremental SAR ATR tasks. Second, a multi-task mixed loss is proposed to continuously generalize on new categories of targets while preserving the reasoning ability on old categories of targets. Experimental results on MSTAR dataset illustrate that the proposed method surpass some state-of-the-art incremental SAR ATR methods.

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