# DISCOVERING NOVEL CATEGORIES IN SAR IMAGES IN OPEN SET CONDITIONS

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## ABSTRACT

In this paper, we deal with the issue of discovering data of novel categories for Synthetic Aperture Radar (SAR) images under open-set conditions. The traditional SAR image classification methods are trained under the closed-set setting where all categories in testing data are seen in training data. It does not always meet the requirements of the real SAR imagery interpretation applications. With a labelled SAR image dataset, we propose a multi-stage approach to effectively pick out images belonging to new classes in another unlabelled dataset and then cluster them into correct number of novel categories. To do so, our pipeline is composed of three major steps: (1) train a powerful feature extractor leveraging both the labelled and unlabelled dataset by semi-supervised inference; (2) identify the unknown data by openset detection; (3) cluster these unknown data based on the features generated by the extractor to discover novel categories. The proposed method is validated on a Sentinel-1 SAR image dataset OpenSARUrban [1].

***Index Terms*—** SAR, Image Classification, Open Set Recognition, Novel Category Discovery, Clustering

## 1. INTRODUCTION

Synthetic Aperture Radar (SAR) is of prominent importance for Earth observation due to its capability of operation in all weather and day-and-night conditions. There is an increasing amount of SAR image data collected and publicly accessible. However, it is still very challenging for SAR image interpretation because of its special active microwave imaging mechanism. Currently, deep neural networks (DNNs), e.g., convolutional neural networks (CNNs), have been widely applied for various SAR image interpretation tasks[2, 3, 1]. Previous methods only work well for closed-set scenarios. With a large amount of SAR data, it is very difficult to annotate the data of all categories, which requires expertise knowledge and consumes much time and labour resource. However, a new unlabelled dataset may contain new data of novel classes that does not appear in training data. Accordingly, it is of practical use to come up with an approach to identify images within a new SAR dataset not belonging to the categories we have known and discover their categories.

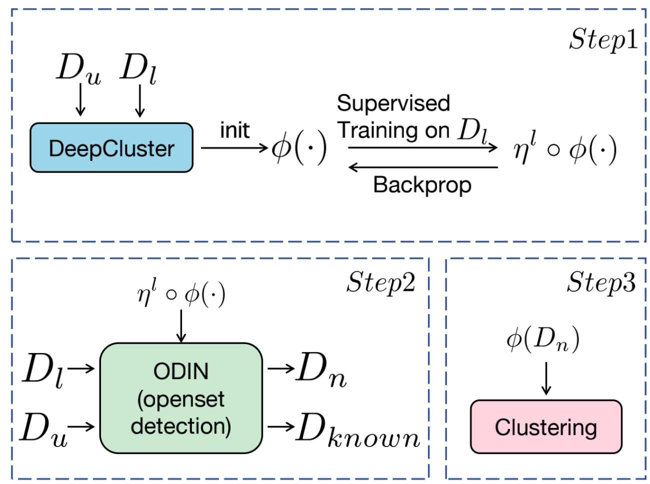


**Fig. 1**. The detailed pipeline of our method to pick out the new category data in SAR image dataset, conducting Step 1,2 and 3 in turn.

Some related work on **Novel Category Discovery (NCD)**, **Openset Detection** and **Representation Learning** can inspire and help us to achieve our goal. Recently, Han *et al.* [4] formalized the issue of NCD and proposed a pipeline based on prior knowledge learned by a different but relative labelled dataset. Han *et al.* [5] also explored using ranking statistics to measure the similarity between images and proposed a method estimating the number of classes in an unlabelled dataset. Zhao *et al.* [6] further ameliorated the work with dual ranking statistics and mutual knowledge distillation. Liang *et al.* [7] proposed an effective baseline for out-of-distribution data detection without requirements for

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pre-trained neural networks. Caron *et al.* [8] addressed the issue of learning useful low-level visual features in a self-supervised way by assigning clustering results as pseudo labels.

Considering that characteristics of SAR images differ considerably from common optical RGB images which often contain speckle and slant-range distortions, therefore in our pipeline, a good feature extracted from raw data is the key foundation to distinguish images from different categories and to all the operations coming after. We design a three-stage method to firstly learn a suitable feature extractor via semi-supervised learning and then conduct openset detection, estimating the number of novel classes and then clustering them all based on the feature generated by the extractor. Compared with the previous methods, our proposed method can not only detect the unknowns but also discover new categories.

## 2. METHODOLOGY

The pipeline of our proposed method is shown in fig. 1. Given a labelled known dataset $D_l = \{(x_i^l, y_i^l); i = 1, 2, ..., N\}$ with the number of classes $C_l$ and an unknown dataset $D_u = \{x_i^u; i = 1, 2, ..., M\}$ with the number of classes $C_u$, where $x_i \in \mathbb{R}^{1\times H\times W}$, our aim is to identify a subset $D_n$ within $D_u$ which belong to novel categories with the number of classes $C_n = C_u - C_l$. The pipeline consists of three major steps detailed below.

### 2.1. Feature Extractor

Now we have two datasets $D_l$ and $D_u$, whose categories are known and unknown respectively. Some works have shown that tasks like clustering or openset detection can perform better in the appropriate high-dimensional feature space [4, 5, 6]. Accordingly, we put forward a two-stage method with CNN architecture to roll out a suitable feature extractor.

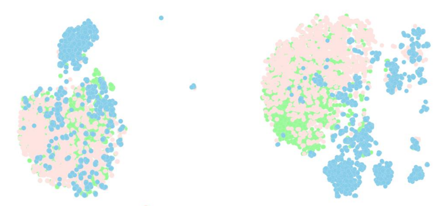
**Self-supervised Learning** To avoid the feature extractor being only sensitive to the labelled data, we use both $D_l$ and $D_u$ to bootstrap the feature extractor $\phi : x \to \phi(x) \in \mathbb{R}^d$ via self-supervised training. Several self-supervised methods have been proposed such as RotNet [9] and MoCo[10]. Given that SAR images are sensitive to imaging operation conditions and the massive number of SAR images require a great amount of resource if we take some contrastive learning methods, we thus use DeepCluster [8] to initialize $\phi$ with the VGG16 [11] architecture. In detail, we iteratively conduct K-Means [12] on $\phi(D_l \cup D_u)$ and assign the clustering results as pseudo labels. In each iteration, we extend $\phi$ with a classification head $\eta^p$: $\mathbb{R}^d \to \mathbb{R}^k$, where a linear layer is implemented to classify the input data into K classes. We use the standard cross-entropy loss:

**Table 1**. The scores for clustering data of 5 classes with the feature extractor before and after being fine-tuned on $D_l$, where ACC refers to Clustering Accuracy, NMI refers to Normalized Mutual Information and ARI refers to Adjusted Rand Index.

| Feature Extractor | Number of Clustering Class | ACC | NMI | ARI |
|---|---|---|---|---|
| before fine-tuning | 5 | 29.54% | 0.127 | 0.110 |
| after fine-tuning | 5 | 43.22% | 0.220 | 0.167 |

$$L_{DeepCluster} = -\frac{1}{N+M}\sum_{1}^{N+M} \log(\eta^p \circ \phi(x_i))_{l_p}$$

where $x_i \in D_l \cup D_u$ and $l_p$ represents the pseudo labels assigned after each clustering.



(a) (b)

**Fig. 2**. Visualization of the distribution of features extracted from $D_n$ by $\phi$. (a) features before fine-tuning; (b) features after fine-tuning.

**Supervised Fine-tuning** Now we have the feature extractor $\phi$ trained by DeepCluster [8] on the union of $D_u$ and $D_l$. However, self-supervised training ignores all labels and therefore cannot leverage the information contained in $\{x_i^l, y_i^l\} \in D_l$. To address the problem, we further extend $\phi$ with a new classification head $\eta^l$: $\mathbb{R}^d \to \mathbb{R}^l$, where we implement a linear layer and a softmax layer coming after. The function $\eta^l \circ \phi(\cdot)$ is fine-tuned on the labelled dataset $D_l$ in a supervised way to learn a classifier for $C_l$ known classes. Here we take a standard cross-entropy loss defined as:

$$L_{supervised} = -\frac{1}{N}\sum_{1}^{N} \log(\eta^l \circ \phi(x_i))_{y_i}$$

where $(x_i, y_i) \in D_l$.

The distribution of features extracted by $\phi$ before and after fine-tuned are visualized in fig. 2(a) and fig. 2(b), where

**Table 2**. The scores for clustering the novel dataset $D_n$.

| Data Process | Data Distribution (known+unknown) | ACC | NMI | ARI |
|---|---|---|---|---|
| $\phi(D_n)$ | 7 + 3 | 58.94% | 0.310 | 0.272 |
| $\phi(D_n)$ | 6 + 4 | 53.55% | 0.256 | 0.169 |
| $\phi(D_n)$ | 5 + 5 | 43.22% | 0.220 | 0.167 |
| raw $D_n$ | 7 + 3 | 41.52% | 0.127 | 0.058 |

we can see $\phi(x)$ distributes more separately after being supervised-trained on $D_l$. We also validate the effectiveness of fine-tuning by experiments shown in table 1, showing that clustering based on $\phi(D_n)$ achieves a better performance after fine-tuning $\phi$ on $D_l$ and self-supervised learning alone cannot effectively leverage information for downstream tasks.

### 2.2. Openset Detection for Novel Data

With the trained feature extractor, we now are ready to pick out the unknown data within $D_u$ that are novel to $D_l$ in the new feature space. With the function $\eta^l \circ \phi(\cdot)$, we use ODIN [7] based on our CNN network to conduct the openset detection, setting $D_l$ as in-distribution images and $D_n$ as out-of-distribution images.

In detail, we adjust the softmax layer in $\eta^l$ with temperature scaling $T$ [7] and for each input we preprocess the image by adding small perturbations [7] before sending the image into our own CNN classifier $\eta^l \circ \phi(\cdot)$. In the end, we recognize each input image from $D_u$ as in- or out-of-distribution data by calculating the new softmax score.

### 2.3. Clustering on Novel Data

Now we have the novel dataset $D_n$ consisting of the unknown data in $D_u$. But before generating them into classes, we need to figure out the number of categories $C_n$ for $D_n$. With the feature extractor $\phi$ we can estimate $C_n$ and set it as K to finally cluster $D_n$ into correct categories by K-Means.

**Estimate the number of K:** A light but effective method to estimate K on some novel dataset was proposed in [4]. We set our $D_l$ as the probe set mixing with $D_n$ and conduct K-Means on the features extracted by $\phi$. By evaluating ACC for the subset $D_l^{rv}$ of $D_l$ and CVI for $D_n$ as defined in [4], we precisely estimate K of $D_n$, using our own feature extractor $\phi$ in the method proposed in [4].

**Clustering:** K-Means is conducted on $\phi(D_n)$ instead of directly on the raw data $D_n$, achieving favorably both in clustering effect and in efficiency.

## 3. EXPERIMENTS

### 3.1. Dataset

We utilize a Sentinel-1 SAR image dataset OpenSARUrban [1] to test our pipeline, which provides 33,358 patches of images covering ten different classes, VH or VV polarized. We only retain images VH-polarized and divide them into $D_l$ and $D_u$ in the ratio of 5:5. And, $D_l$ covers 7 classes whereas $D_u$ covers the total 10 classes, including the 7 classes contained in $D_l$. For comparison, we also test the pipeline with the number of classes in $D_l$ being 6 and 5.

### 3.2. Training details

For DeepCluster stage in Section2.1, we set K as 512 and the network parameters initialized to the original VGG16 network. The training is on the union of $D_l$ and $D_u$ for 100 epochs. fig. 3(a) shows the evolution of Normalized Mutual Information(NMI) on the previous assignment of pseudo labels after each loop, defined as:

$$NMI(Y, \bar{Y}) = \frac{I(Y, \bar{Y})}{\sqrt{H(Y)H(\bar{Y})}}$$

where $I$ measures the mutual information between assigned labels $Y$ and predicted labels $\bar{Y}$, with H the entropy. We can see that NMI increases during our training and it means the features we extract progressively capture information related to object classes during the training.

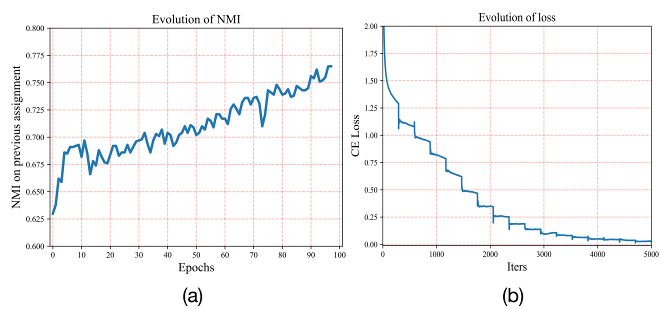



**Fig. 3**. The training process of self-supervised learning and supervised learning.

When fine-tuning the feature extractor $\phi$ along with the classification head $\eta^l$, we optimize the network with standard cross-entropy loss for 5000 iterations, updating the weights both in $\phi$ and $\eta^l$. The process is shown in fig. 3(b). For step2 and step3 in Fig.2, we keep the setting identical to the original method except for using our own CNN feature extractor $\phi$ and classification head $\eta^l$, keeping true positive rate (TRP) as 95% in ODIN for step2.

### 3.3. Results and Discussion

We estimate the number of categories for the novel dataset $D_n$ and then conduct K-Means on $\phi(D_n)$. For comparison, we also test K-Means directly on $D_n$ and find our methods outperforms it after previously extracting the feature with $\phi$. The results are reported in table 2, where we can see clustering performs better on the features extracted by our $\phi$, considering the extractor $\phi$ is also fundamental to openset detection and estimating the number of novel categories. We measure the clustering performance on $D_n$ by the indexes of Accuracy (ACC), Normalized Mutual Information (NMI) and Adjusted Rand Index (ARI) [13], the last of which is defined as:

$$ARI = \frac{RI - E(RI)}{\max(RI) - E(RI)}$$

with

$$RI = \frac{TP + TN}{TP + FP + TN + FN}$$

where TP,TN,FP,FN refer to True Positive, True Negative, False Positive, False Negative respectively.

Also, we find the method proposed in [4] to estimate K can work with a lower error rate when using our feature extractor, where we can estimate the number of novel categories $D_n$ accurately to be 3,4 and 5, data distribution as described in table 2.

In this work, we mainly focus on the pipeline itself that can effectively extract the features of SAR images and help discover the new categories. Accordingly, we choose the classical but simple architecture VGG16 as our backbone, instead of trying some more advanced and complex networks.

## 4. CONCLUSION

In this paper, we roll out a multi-stage pipeline to find out data with novel categories in unlabelled SAR dataset and cluster them into correct number of categories, based on an effective feature extractor learned from both labelled and unlabelled data. We conduct validation experiments on a Sentinel-1 SAR image dataset and have proven our method to be effective.

## 5. REFERENCES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