Sparse Robust Filters for Scene Classification of Synthetic Aperture Radar (SAR) Images

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Abstract—With the increasing resolution of Synthetic Aperture Radar (SAR) images, extracting their discriminative features for scenes classification has become a challenging task, because SAR images are very sensitive to target aspect brought by shadowing effects, interaction of the signature with the environment, and so on. Moreover, SAR images are remarkably polluted by the multiplicative speckle noise, which makes the conventional feature extractors **inefficient**. In this paper we advance new Sparse Robust Filters (SRFs) for automatic learning of discriminant features of scenes. A Hierarchical Group Sparse Coding (HGSC) model is proposed to learn a set of sparse and robust filters, to capture the multiscale local descriptors that are robust to noises. Some experiments are taken on a TerraSAR-X images dataset (in the middle of the Swabian Jura, the Nördlinger Ries, HH, observed on July, 2007), and a Moving and Stationary Target Acquisition and Recognition (MSTAR) dataset, to evaluate the performance of **our proposed method**. The experimental results show that **our method** can achieve higher **classification** accuracy compared with other related approaches.

Index Terms—Scene classification; synthetic aperture radar; sparse robust filters; hierarchical group sparse coding

I. INTRODUCTION

Synthetic Aperture Radar (SAR) imaging technology has made rapid developments in recent years. Enormous amount of high spatial SAR images are collected every day from the increasing number of launched imaging platforms, which **contain much** important information for the subsequent decision in both the military and civil applications. As a consequence, these huge volume of SAR data need a **rapid and** automatic understanding and interpretation by computers. For more efficient interpretation of SAR data, one often **need** to first recognize the semantic category of a scene and then discover the semantically meaningful information contained within **scenes** [1-5], for target detection, target segmentation, target recognition and so on. Consequently, scene classification has been one of the most fundamental tasks in SAR images understanding and interpretation [6-9].

Scene classification of SAR images is a **challenging** task because one scene often **covers** multiple land-cover classes or ground objects. Feature extraction is the first and most critical step in the scene classification, whose aim is to find a

highly discriminative descriptor to predict the category of the scene. It can remarkably influence the classification results and the subsequent understanding of SAR images. Manually designing feature representations is very popular in the feature extraction of SAR images [9-18]. Early feature extractors of SAR images aim to develop a single unified model to jointly describe all aspects of the scene [9-10]. However, a scene can be described in many ways or from multiple views, including regions, geometric structures, textures, and so on [11-18]. Some texture features, such as gray-level co-occurrence matrix (GLCM) [1], Gabor filter [2], Gaussian Markov random field (GMRF) [3] and some complex structure in a local context [6], have been used for extracting discriminative features. Sparse coding is also adopted to encode the image scenes by a set of generated basis functions. Recently, researches on the description of SAR images have proceeded along many separate trajectories [19-23]. For example, Scale-Invariant-Feature-Transform (SIFT)-based feature descriptors and sparse coding (SIFT+SC) proved to output the state-of-the-art results. However, manually designing a combination of various types of features is a boring “feature engineering”. Moreover, the feature extraction of SAR images is especially difficult, for the following reasons: 1) SAR images are corrupted by multiplicative speckle noises due to random interference of electromagnetic waves, and more land-covers or ground objects are contained in a scene compared with natural images; 2) SAR images are very sensitive to target aspect brought by shadowing effects, interaction of the signature with the environment, and so on; 3) The increasing resolution of SAR images makes the spatial and structural information in the image more complex. These characteristics of SAR images make the traditional low-level feature extractors (e.g., pixels, texture, and shapes) insufficient for extracting highly discriminative features and achieving satisfactory classification results.

Very recently one of the trends in image descriptors is to learn a high-level summary or representation of an image without explicitly describing the context within it. One of its realizations is the unsupervised feature learning, which has been shown to be effective at learning representations of images, videos and audios [24-37]. Many deep learning models, including Auto-Encoders (AEs) [28], Restricted Boltzmann Machines (RBMs) [38] et.al, have been developed for learning low-dimensional feature representations to reduce the data dimensionality. Although these approaches can avoid manually designing discriminative features, they are always challenging to implement for the requirement of tuning various parameters. For example, RBMs often has half a dozen parameters and an intractable objective function, which makes it hard to tune and converge [38-39].

In order to well understand computational principles or neural mechanisms of the feature extraction process, one should expand our view of biological underpinnings of visual sensing. Consequently, combining purely computational models with biological evidences is very promising for deriving a set of sophisticated features from complex scenes. Recently sparse representation or coding has been developed to explain early visual cortex as an efficient means of

coding [40-43]. Sparse coding has found successful applications in machine learning, which can approximate data using a few non-zero coefficients (features) and provide insights into designing new algorithms based on optimizing for desirable properties of features [19-22]. For the characteristic of simple principle, robustness to noise, and flexible representation, sparse coding is potential to process complex and heavily polluted SAR images. By simulating the sparse coding mechanism of visual neuron, we can learn sets of over-complete bases to represent SAR data efficiently. Moreover, visual organization rules state that visual forms are not only sparse, but also hierarchical or deep. In recent years, the neocortex of the mammalian brain proves to organize in a complex layered structure of neurons. The past few years have witnessed prosperity of establishing deep architectures for modeling complex structured data [1-3]. Therefore, deep architectures are useful to solve complex cognition tasks, where the multiscale information of a complex scene can be captured via hierarchical learning.

In this paper, we combine the sparsity/selective characteristic and deep architectures of the visual organization rules together, and use these biological evidences to develop a simple and efficient sparse feature learning model to describe SAR image scenes. In our method, we cast a two-fold sparsity on the discriminative features, and extend the sparse coding to the multiscale case, to develop a Hierarchical Group Sparse Coding (HGSC) model for representing data and making it easier to extract useful information when building classifiers. The Treves-Rolls [44-45] measure is employed to characterize the sparsity of features, and a total variation regularizer is cast on the filters optimization to reduce the noise. Consequently, the proposed HGSC can not only exploit the discrimination between different classes of scenes, but also robust to intrinsic speckle noises. Some experiments are taken on a TerraSAR-X images dataset (in the middle of the Swabian Jura, the Nördlinger Ries, HH, observed on July, 2007), and a Moving and Stationary Target Acquisition and Recognition (MSTAR) dataset, to evaluate the performance of our proposed method. The experimental results show that our proposed method can achieve higher classification accuracy when compared with other related approaches.

The rest of this paper is organized as follows. Section II introduces the proposed sparse robust filters. Section III reports the experimental results, with a comparison with some related feature extraction approaches. Conclusions are finally given in Section IV.

II. SPARSE ROBUST FILTERS (SRFs) FOR SCENE CLASSIFICATION

Given one SAR image being certain classes of a scene, we first partition it into some small $\sqrt{n} \times \sqrt{n}$ patches, and then convert it into an n -dimensional vector $\mathbf{x}_i (i = 1, \dots, N)$, where N is the number of patches. Then the whole image can be

described as a patch matrix $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_N] \in \mathbf{R}^{n \times N}$, whose column is a patch or example. In our method, we first assume that the features of $\mathbf{X}$ are generated through some deterministic nonlinear transformation, that is, the j -th feature of the sample $\mathbf{x}_i$ is calculated by $f_i^j = \phi(\mathbf{w}_j^T \mathbf{x}_i) (i = 1, \dots, N; j = 1, \dots, d)$, where $\phi(\cdot)$ is a nonlinear transformation function and $\{\mathbf{w}_j\}_{j=1}^d$ are a set of projection functions or filters to generate features. Combing the features f_i^j together, we can derive a feature matrix $\mathbf{F}$,

$$\mathbf{F} = \phi(\mathbf{WX}) = [\mathbf{f}_1, \dots, \mathbf{f}_N] = \left[(\mathbf{f}^1})^T, \dots, (\mathbf{f}^d})^T \right]^T \quad (1)$$

where $\mathbf{W} = [\mathbf{w}_1, \dots, \mathbf{w}_d] \in \mathbf{R}^{d \times n}$ and $\mathbf{F} \in \mathbf{R}^{d \times N}$ in the formula (1). In the feature matrix $\mathbf{F}$, each entry f_i^j is the activity of feature j on the i -th example. Each column in $\mathbf{F}$ is denoted as $\mathbf{f}_i \in \mathbf{R}^d (i = 1, \dots, N)$ (d is the number of features) and each row is denoted as $\mathbf{f}^j \in \mathbf{R}^N (j = 1, \dots, d)$. As mentioned in the introduction, a computational feature learning model should not only be descriptive, mathematical, algorithmic/computational about the feature calculation process, but also attempt to mimic and explain visual attentive behaviors, such as the sparse characteristic and deep architectures of the visual organization rules. In the following some desirable properties of the feature matrix will be discussed.

A. Two-fold Sparsity of Features

The neuron activations in the human brain have the characteristic of sparsity. First, only limited number of neurons are active when one sees a scene. Second, for a given neuron, it does not response to the whole scene but a local region. In our method, this two-fold sparsity of the feature matrix is explored, which can be summarized as the sparsity along the rows and columns respectively. Concretely, only a small number of features of one sample are remarkable while others are not, that is, each $\mathbf{f}_i$ in the feature matrix $\mathbf{F}$ should be sparse. On the other hand, in order to keep the discrimination ability of features, only a small number of examples are active when receiving multiple examples, that is, each $\mathbf{f}^j$ in the feature matrix $\mathbf{F}$ should be sparse. In our work, the feature matrix is considered to have this two-fold sparsity.

Moreover, our method casts an assumption that each feature is equally active on the feature matrix $\mathbf{F}$, via dividing each feature by its 2-norm across all examples, that is, $\|\mathbf{f}^j\|_2 = 1$. Each sample is considered to have unit length, i.e., $\|\mathbf{f}_i\|_2 = 1$. Consequently, finding the features with two-fold sparsity can be reduced to the following optimization problem,

$$\begin{cases} \min_{\mathbf{f}} \sum_i \|\mathbf{f}_i\|_0 + \sum_j \|\mathbf{f}^j\|_0 \\ s.t. \|\mathbf{f}_i\|_2 = 1; \|\mathbf{f}^j\|_2 = 1 \end{cases} \quad (2)$$

Replacing $\mathbf{F} = \phi(\mathbf{WX})$ into the formula (2), we can reformulate the formula (2) as,

$$\begin{cases} \min_{\mathbf{W}} \|\phi(\mathbf{WX})\|_{row,0} + \|\phi(\mathbf{WX})\|_{col,0} \\ s.t. \quad \|\phi(\mathbf{W}\mathbf{x}_i)\|_2 = 1; \quad \|\phi(\mathbf{w}_i\mathbf{X})\|_2 = 1, \quad \forall i \end{cases} \quad (3)$$

It is a Group Sparse Coding (GSC) model for representing data and extracting useful information. As soon as the solution to [the formula \(3\)](#) is obtained, we can obtain a group of sparse filters $\{\mathbf{w}_i\}$ from $\mathbf{W}$.

B. Hierarchical Sparse and Robust Filters

Because SAR images are often heavily polluted by speckle noises, the learned filters cannot reveal the low-level features such as edges, contours and texons. In our work we develop a set of sparse and robust filters, to reduce the influence of intrinsic noises on the feature extraction. The noises in the image would generate some unwanted features and degrade the classification results. So in our method, a total variation regularizer is cast on the filters optimization to make them robust to [noises](#). That is, we hope the derivation of $\phi(\mathbf{WX})$ can be minimized, which can be written as, $\sum_i \|\nabla \phi(\mathbf{W}\mathbf{x}_i)\|_1$. The optimization of the L1 norm of gradients will reduce the unwanted singular features, which is some like a nonlinear denoising filtering. Introducing this regularizer into the [GSC](#) model in [the formula \(3\)](#), we can obtain,

$$\begin{cases} \min_{\mathbf{W}} \left(\|\phi(\mathbf{WX})\|_{row,0} + \|\phi(\mathbf{WX})\|_{col,0} \right) + \lambda \|\nabla \phi(\mathbf{WX})\|_1 \\ s.t. \quad \|\phi(\mathbf{W}\mathbf{x}_i)\|_2 = 1; \quad \|\phi(\mathbf{w}_i\mathbf{X})\|_2 = 1, \quad \forall i \end{cases} \quad (4)$$

In this paper, an Alternating Direction Method of Multipliers (ADMM) algorithm [52] is advanced to solve (4). By introducing a new variable $\mathbf{H}$, the formula (4) is first changed to,

$$\min_{\mathbf{W}, \mathbf{H}} \left(\|\phi(\mathbf{WX})\|_{row,0} + \|\phi(\mathbf{WX})\|_{col,0} \right) + \lambda \|\nabla \phi(\mathbf{HX})\|_1 + \sum_i \left[\|\phi(\mathbf{W}\mathbf{x}_i)\|_2 - 1 \right]^2 + \sum_i \left[\|\phi(\mathbf{w}_i\mathbf{X})\|_2 - 1 \right]^2 + \|\mathbf{W} - \mathbf{H}\|^2 \quad (5)$$

The optimization problem is divided into two sub-problems: the optimization of $\mathbf{W}$ and $\mathbf{H}$.

[In order to solve \(5\), firstly](#) we fix $\mathbf{H}$ and optimize $\mathbf{W}$ by solving (6),

$$\min_{\mathbf{W}} \left(\|\phi(\mathbf{WX})\|_{row,0} + \|\phi(\mathbf{WX})\|_{col,0} \right) + \sum_i \left[\|\phi(\mathbf{W}\mathbf{x}_i)\|_2 - 1 \right]^2 + \sum_i \left[\|\phi(\mathbf{w}_i\mathbf{X})\|_2 - 1 \right]^2 + \|\mathbf{W} - \mathbf{H}\|^2 \quad (6)$$

It can be achieved using the canonical greedy layerwise approach [46-47]. Then we fix $\mathbf{W}$ and optimize $\mathbf{H}$ by solving [53],

$$\min_{\mathbf{H}} \lambda \|\nabla \phi(\mathbf{HX})\|_1 + \|\mathbf{W} - \mathbf{H}\|^2 \quad (7)$$

The two variables update iteratively to derive a solution to (4), then we can obtain a group of sparse robust filters $\mathbf{W}^1, \mathbf{W}^2, \dots$. Moreover, this process is cascaded to develop a Hierarchical Group Sparse Coding (HGSC) model for hierarchically representing patches, as shown in fig.1. When the features are extracted, they are processed by a maximal pooling to input into the next layer.

Fig.1 Generation of Hierarchical Sparse and Robust Filters via HGSC

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, some experiments are taken to investigate the performance of our proposed method. Some experiments are carried to evaluate our method and compare it with some related approaches in the literature, including: 1) Principal Component Analysis (PCA)[7]; 2) Sparse Coding based feature extraction (SC) [20]; 3) Contextual Classification Algorithm (CCA) [22]; 4) CRFs [23]; 5) AE [28]; 6) RBM [38]. In the comparative deep networks, both AE and RBM can present the best results when 8×8 patches are used, so in our method we choose $n=64$ for a fair comparison, and the number of patches $N = (256 \times 256) / (8 \times 8) = 1024$. Three layers are used for feature extraction and a linear SVM is used for the classification, $\phi(x) = \sqrt{\varepsilon + x^2}$, $\varepsilon=0.1$. In this section, we applied sparse filtering to learn features from 5000 patches that are randomly sampled from the SAR images in two datasets. In SVM, C is chosen by hold-out cross-validation. For each image size, we learn a complete set of features (i.e., equal to the number of input dimensions). In the comparative methods, we set the layers of AE and RBM networks as three, and the number of filters in these two networks is also the same with that of our method. AE is implemented as described in Coates et al. [49]. In the sparse coding method, we used code from [50] for determining the coefficients. In CCA and CRFs, we use the parameters suggested in the literatures. The simulations of different methods are carried out in MATLAB 7.10.0(R2010a) environment running in Core 2 Quad, 2.99-GHZ CPU with 2-GB RAM. 30 independent experiments are undertaken, and the average results are calculated for a comparison.

A. Datasets

Dataset 1: The performance of our proposed method is first tested on a TerraSAR-X images database containing 10600 scene images (in the middle of the Swabian Jura, the Nördlinger Ries, HH, observed on July, 2007). In the dataset there are six classes of scenes, including city, airport, farmland, bridge, mountain, and water, some samples are shown in fig.2. All the images in this dataset are of size 256×256 .

Fig.2 Some example samples in the database.

Dataset 2: The second dataset is a Moving and Stationary Target Acquisition and Recognition (MSTAR) dataset. These SAR images are collected in spotlight mode at $0.3m \times 0.3m$ resolution with HH polarization by the Sandia National Laboratory X-band SAR sensor. And it contains 10 classes of military vehicles. Each of the targets has views at 15° and 17° depression angles [51][54]. In our experiments, we use three types of vehicles, including BMP2 (tank), BTR70 (armored car) and T72 (tank), to evaluate the performance of our proposed scheme. The data in depression 17° are used for training and the rest for testing. The number of training and test samples of each target is shown in Table I.

TABLE I
THE NUMBER OF TRAINING AND TESTING SAMPLES FOR EACH TYPE OF TARGET

Vehicle(17°)	#Training Samples	#Testing Samples	Vehicle(17°)	#Training Samples	#Testing Samples
BMP2(S-C9563)	233	195	BMP2(S-C 21)	233	196
BMP2(S-C 9566)	232	196	BTR70(SN-C71)	233	196
BMP2(S-C 21)	233	196	T72(SN-132)	232	196
BTR70(SN-C71)	233	196	T72(SN-812)	231	195
T72(SN-132)	232	196	T72(SN-S7)	228	191
T72(SN-812)	231	195	BMP2(S-C 9566)	232	196
T72(SN-S7)	228	191	BMP2(S-C 21)	233	196
BMP2(S-C 9566)	232	196			

Some example training images (including nine images in dataset 1 and three types of vehicles' images in dataset 2) are shown in Fig.3.

Fig.3 Training examples in dataset 1 and dataset 2

Experiment 1: Classification results on Dataset 1

In this test, we classify this dataset by different methods and change the number of training samples. The training samples of each class take 10, 20, 40, 60 respectively, and the number of the total training samples is 60, 120, 240 and 360 respectively. The experiments are taken under the condition in section III.A. The classification accuracy of PCA[7], SC[20], CCA[22], CRFs[23], AE[28], RBM[38] and our method are shown in table II. From it we can see that for the seven methods, the classification accuracy increases with the number of training samples. Compared with the shallow models such as the PCA[7], SC[20], CCA[22] and CRFs[23], the hierarchical models (including AE, RBM and our method) can obtain higher recognition accuracy, for exploring the deep properties of organization in a complex layered structure of neurons. Moreover, our method can achieve comparable classification accuracy with the two deep models when there are small number of training samples. With the increase of the number of training samples, our method can obtain accurate classification results than the two deep networks, for learning a set of sparse and robust filters, to capture the multiscale local descriptors that are robust to noises.

TABLE II
The recognition accuracy (%) for different approaches

#training samples	PCA[7]	SC[20]	CCA[22]	CRFs[23]	AE[28]	RBM[38]	Our method
60	70.22	71.90	73.04	72.32	78.47	80.33	79.48
120	71.24	74.39	75.88	74.90	82.11	83.89	83.27
240	74.27	76.02	77.36	75.25	84.49	89.92	90.41
360	76.33	79.47	80.04	78.93	86.52	90.26	92.35

B. Experiment 2: Classification results on Dataset 2

In this experiment, we classify the dataset 2 by using different methods (including PCA[7], SC[20], CCA[22], CRFs[23], AE[28], RBM[38] and our method) under the condition described in section III.A. For all the methods, 100 images per class are taken from the dataset and used as training samples. Fig.4 plots the confusion matrix of the classification result by our method. From fig.4 we can see that our method can achieve accurate recognition for the seven

types of objects.

BMP2(S-C9563)	BMP2(S-C 9566)	BMP2(S-C 21)	BTR70(SN-C71)	T72(SN-132)	T72(SN-812)	T72(SN-S7)
183.00	4.00	4.00	0.00	2.00	1.00	1.00
3.00	185.00	5.00	1.00	0.00	2.00	0.00
3.00	2.00	189.00	0.00	1.00	1.00	0.00
1.00	3.00	1.00	189.00	0.00	1.00	1.00
0.00	1.00	2.00	0.00	190.00	2.00	1.00
0.00	1.00	1.00	0.00	2.00	188.00	3.00
0.00	1.00	0.00	0.00	2.00	2.00	186.00

Fig.4 The confusion matrix of the classification result by our method

Moreover, we compare the classification results of PCA[7], SC[20], CCA[22], CRFs[23], AE[28], RBM[38] with our proposed method, and the results are shown in fig.5. From it we can see that our method can achieve more accurate classification than both the shallow models and two deep networks. Moreover, the deep models outperform the other methods remarkably for employing hierarchical model. In our method, SRFs can automatically learn the discriminant features of scenes that are robust to noise, by simulating the sparse coding and hierarchical mechanism of visual neuron. Moreover, by adding a regularizer in filters learning, our method can present better results than the other two deep networks.

Fig.5 The comparative results of different methods

III. CONCLUSIONS

Inspired by the recently developed sparse coding, in this paper a new Sparse Robust Filters (SRF) based feature extraction approach is proposed. Hierarchical sparse representation is utilized to extract the discriminant features of

scenes, and sparse and robust filters are designed to capture the multiscale local descriptors robust to noise. Some experiments are taken on a TerraSAR-X images dataset and a MSTAR dataset, to evaluate the performance of our proposed method. The experimental results show that our proposed method can achieve higher recognition accuracy compared with other related approaches.

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