PolSAR Image Classification using Discriminative Clustering

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***Abstract*—This paper presents a novel unsupervised image classification method for polarimetric synthetic aperture radar (PolSAR) data. The proposed method is based on a discriminative clustering framework that explicitly relies on a discriminative supervised classification technique to perform unsupervised clustering. To implement this idea, we design an energy function for unsupervised PolSAR image classification by combining a supervised softmax regression model with a Markov Random Field (MRF) smoothness constraint. In this model, both the pixel-wise class labels and classifiers are taken as unknown variables to be optimized. Starting from the initialized class labels generated by Cloude-Pottier decomposition and K-Wishart distribution hypothesis, we iteratively optimize the classifiers and class labels by alternately minimizing the energy function w.r.t. them. Finally, the optimized class labels are taken as the classification result, and the classifiers for different classes are also derived as a side effect. We apply this approach to real PolSAR benchmark data. Extensive experiments justify that our approach can effectively classify the PolSAR image in an unsupervised way, and produce higher accuracies than the compared state-of-the-art methods.**

***Index Terms*—PolSAR image classification, discriminative clustering, softmax regression model, MRF.**

I. INTRODUCTION

POLSAR is one of the most advanced and important environmental monitoring techniques due to its all-time and all-weather observation character and abundant high-resolution target information. The successful applications of PolSAR rely heavily on PolSAR image interpretation techniques, during which PolSAR image classification is one of the most important ones.

Machine learning approach has been a dominant approach in PolSAR image classification task in recent years. Considering whether a training set is utilized, they can be categorized into supervised classification methods [1]–[3] and unsupervised classification methods [4]–[10]. With a good training set, supervised methods can achieve more precise and reliable classification results than unsupervised algorithms. However, ground truth class labels are not always available for PolSAR images, and the homogeneity and integrality of the selected training sets cannot be guaranteed through manual operation in many cases. Unsupervised methods are fast and totally automatic. However, the classification accuracy relies heavily on the design of the unsupervised algorithm. It is still a challenging task to design an effective unsupervised algorithm for PolSAR image classification.

In this work, we introduce a novel discriminative clustering-based model [11], [12] to PolSAR image classification, which solves an unsupervised classification problem taking advantage of the discriminative learning power of supervised classification method. We design an energy function combing a cross entropy loss term and a class label smoothness term. The first term is responsible for learning classifiers to discriminate different classes and the second term enforces label smoothness. The classifiers and class labels are both taken as variables to be optimized. Given a rough initialization of labels based on the Cloude-Pottier decomposition theory and K-Wishart polarimetric statistical distribution, we propose to iteratively and alternately optimize the classifiers and class labels. The optimization of classifiers is implemented by solving a softmax regression problem, and the optimization of class labels boils down to a combinatorial optimization problem effectively solved by a belief propagation algorithm. By alternately optimizing the classifiers and class labels in an iterative manner, the class labels will be updated step by step until the termination criterion is met.

II. THE PROPOSED METHOD

A. Overview of Our Method

We now present the basic pipeline of the proposed discriminative clustering-based PolSAR image classification method. Given a PolSAR image with N pixels, the input of each pixel is a coherency matrix T. A 58-dimensional pixel-wise feature vector x_i for each pixel $i (i \in \{1, \cdots N\})$ is extracted from coherency matrix T. The algorithm is designed to assign class label $y_i (y_i \in \{1, \cdots K\})$ to each pixel i, where there are K classes in total. We further denote $X = \{x_i\}$ and $Y = \{y_i\}$ in the following sections.

Taking the AIRSAR Felvoland PolSAR image for example, Fig. 1 illustrates an overview of the proposed PolSAR image classification approach. It comprises of three steps. (1) Feature extraction: pixel-wise feature vectors X are extracted from coherency matrix T through implementing mathematical transforms and target decompositions on it; (2) Initialization: an initialized class label map is produced as the input of the following step; (3) Discriminative clustering: an iterative optimization algorithm is run to optimize the discriminative clustering-based model for refining the classification label.

B. Discriminative Clustering-based Model

We define a novel loss function for the unsupervised PolSAR image classification, and the class labels Y and classifiers

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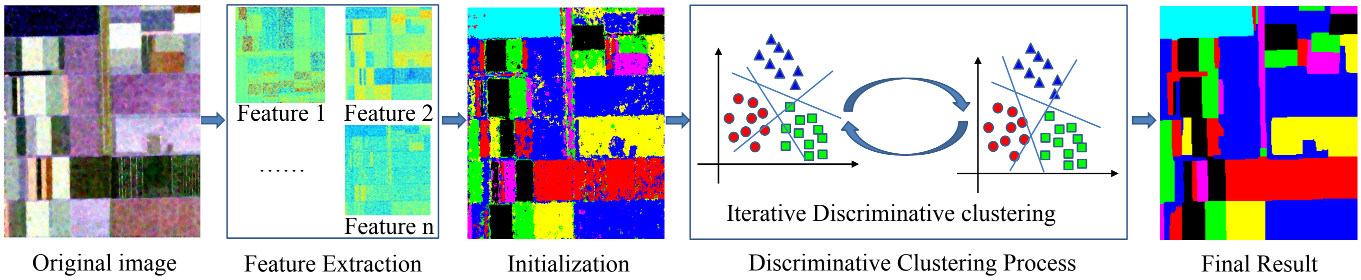

Fig. 1. Overview of our PolSAR image classification method based on discriminative clustering.

W can be derived by minimizing it. The loss function is defined as:

$$E(Y,W|X) = E_c(Y,W|X) + E_s(Y,W|X), \tag{1}$$

where $E_c(Y,W|X)$ is named as discriminative clustering term, and $E_s(Y,W|X)$ is the label smoothness term.

1) Discriminative clustering term: The discriminative clustering term $E_c(Y,W|X)$ is defined following the formula of softmax regression model, which is defined as:

$$E_c(Y,W|X) = L(Y,W|X) + R(W), \tag{2}$$

where $L(Y,W|X)$ is the softmax loss function, and $R(W)$ is the regularization item. The softmax loss function is defined as the cross-entropy loss:

$$L(Y,W|X) = -\sum_{i=1}^{N}\sum_{j=1}^{K}\frac{1}{N_j}1\{y_i=j\}\log\frac{e^{W_j^T x_i}}{\sum_{l=1}^{K}e^{W_l^T x_i}}, \tag{3}$$

where $1\{y_i=j\}$ is an indicator function that equals to 1 when $\{y_i=j\}$ is true, and equals to 0 otherwise.

To prevent possible over-fitting caused by data noise and outliers, a L2-norm regularizer $R(W)$ is incorporated after the cross-entropy loss, which is defined as:

$$R(W) = \alpha_c\sum_{i=1}^{K}\sum_{j=1}^{M}W_{ij}^2, \tag{4}$$

where α_c is the regularization parameter and M is the number of vector dimension. With this convex regularization term (for any $\alpha_c > 0$), the loss function E_c is strictly convex and guaranteed to have a unique solution theoretically. In this work, α_c is fixed as 5×10^{-5}.

2) Label smoothness term: The label smoothness term $E_s(Y,W|X)$ is defined to enforce that the neighboring pixels in an image should have similar class labels. We define it as:

$$E_s(Y,W|X) = \alpha_s\sum_{i=1}^{N}\sum_{j\in\mathcal{N}(i)}\mathcal{S}_{ij}, \tag{5}$$

where α_s is the label smoothness factor, and $\mathcal{N}(i)$ is the set of neighboring pixels of pixel i. $\mathcal{S}_{ij}$ is defined as:

$$\mathcal{S}_{ij} = |y_i - y_j|\exp\left(-\frac{\|v_i - v_j\|_2^2}{2\sigma}\right), \tag{6}$$

where v_i is a feature vector located at pixel i, which should be selected as the features significantly changing values across the edges in image. We take it as combination of Pauli matrix components in this work. σ is the mean squared distance between features of two adjacent pixels i and j. Label smoothness term tends to make adjacent pixels have the same label, and encourages the label boundaries to align with strong edges. For neighboring pixels i and j within flat regions, $\exp(-\frac{\|v_i-v_j\|_2^2}{2\sigma})$ in Eq. (6) is large, then minimizing $\mathcal{S}_{ij}$ strongly enforces that labels y_i and y_j should take same value. But for neighboring pixels across strong edges, $\exp(-\frac{\|v_i-v_j\|_2^2}{2\sigma})$ is smaller (or even near to zero), thus the discrepancy between labels of neighboring pixels i and j is allowable in optimization.

C. Optimization

The classifiers W for different classes and the class labels Y can be solved by minimizing the loss function defined in Eq. (1). This optimization problem can be decomposed into two subproblems which could be solved alternately and iteratively.

1) Subproblem 1: Solve W with fixed Y.

The purpose of *subproblem 1* is to learn classifiers W from the currently estimated class labels Y which act as fixed variables in this subproblem. Therefore, in an iteration t, the currently estimated class labels are taken as the initialized class labels for iteration $t=1$, and the class labels estimated in iteration $t-1$ for iteration $t>1$.

In this subproblem, since class labels Y are taken as constant, the loss function in Eq. (1) can be re-written as:

$$\begin{aligned} E(W|X,Y) \quad = \quad & -\sum_{i=1}^{N}\sum_{j=1}^{K}\frac{1}{N_j}1\{y_i=j\}\log\frac{e^{W_j^T x_i}}{\sum_{l=1}^{K}e^{W_l^T x_i}} \\ & + \quad \alpha_c\sum_{i=1}^{K}\sum_{j=1}^{M}W_{ij}^2, \end{aligned} \tag{7}$$

We optimize W by minimizing the above softmax regression problem. It can not be solved with a closed-form solution, and thus an iterative optimization algorithm is employed. we use L-BFGS [13] optimization algorithm to minimize $E(W|X,Y)$ in Eq. (7) .

2) Subproblem 2: Solve Y with fixed W.

Subproblem 2 aims to estimate pixel-wise class labels Y. Label smoothness constraint is taken into account in this process.

Since classifiers W are taken as constant, the loss function in Eq. (1) can be re-written as:

$$E(Y|X,W) = -\sum_{i=1}^{N}\sum_{j=1}^{K}\frac{1}{N_j}1\{y_i=j\}\log\frac{e^{W_j^T x_i}}{\sum_{l=1}^{K}e^{W_l^T x_i}} + \alpha_s\sum_{i=1}^{N}\sum_{j\in\mathcal{N}(i)}|y_i-y_j|\exp\left(-\frac{\|v_i-v_j\|_2^2}{2\sigma}\right) \tag{8}$$

Class labels Y can be solved by minimizing Eq. (8) with fixed W. This label assignment problem is a combinatorial optimization problem in essence. The model in Eq. (8) can be regarded as an MRF model. Labeling problem in an MRF has been demonstrated to be a NP-hard problem. BP [14] algorithm is employed in this work. The advantage of BP algorithm is that labeling information can be quickly propagated across the image. The scheme of "up-down-left-right" message passing schedule makes BP algorithm converge fast.

D. Features and Initialization

As shown in Table 1, a 58-dimensional feature vector is extracted from PolSAR data, including intensities and phases of coherence matrices, the ratios between different intensity channels in three different polarimetric ways, SPAN, and decomposition parameters derived from Pauli, Cloude-Pottier and Freeman decomposition.

For initialization, Cloude-Pottier decomposition is employed first to generate initialized class labels. Then a maximum likelihood classifier based on K-Wishart polarimetric statistical distribution is then applied to refine the classification map.

III. Experiments

A. Experimental Data and Settings

Experiments are carried out on one real PolSAR image for Flevoland area in Netherlands, which was acquired by NASA/JPL AIRSAR on August 16, 1989. The size of the image we used is 300×270. The ground truth class labels and the corresponding color codes are shown in Fig. 2(a) and (b) respectively. As observed from the ground truth class labels of the Flevoland area data, there are seven classes in the PolSAR image including bare soil, barley, lucerne, peas, potatoes, beet and wheat.

Fig.2(c)-(h) give the classification results of the proposed method and other 5 state-of-the-art methods. The proposed method uses supervised softmax regression and numerous features to carry out unsupervised classification, and many misclassification artifacts in the initialized label map are rectified during the iterative optimization. The introduced smoothness constraint using MRF model leads to a smoother classification map. For the above reasons, compared with the other five methods, the proposed method shows a better performance with lower misclassification ratio and better visual effect. Table II gives the overall classification accuracy (CA) values of the proposed method with other 5 methods. It can be seen that overall CA value of the proposed method is 13.46%, 7.23%, 8.89%, 10.75% and 3.19% higher than the compared methods respectively.

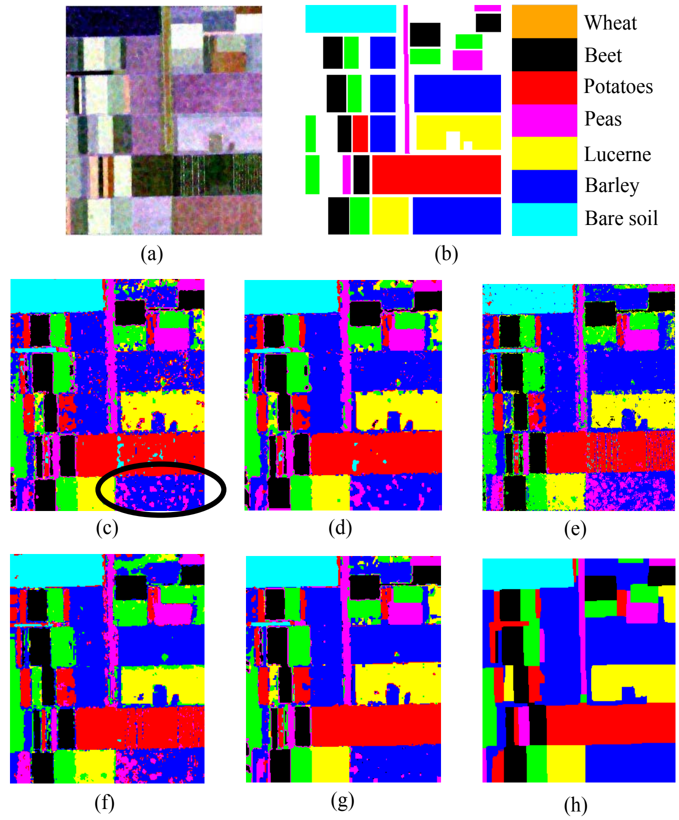

Fig. 2. Class labels of Flevland area data with different methods. (a) Original image of Flevoland area. (b) Ground truth class label of the image. (c) $H/\bar{\alpha}$-Wishart classifier [7]. (d) Wishart MRF classifer [8]. (e) Freeman Wishart classifier [5]. (f) Power Entropy and Copolarized Ratio classifier [9]. (g) Wishart TMF classifier [10]. (h) The proposed method.

IV. Conclusion

A novel unsupervised classification method based on discriminative clustering is presented in this paper. The contribution of our work is that we take advantage of supervised learning technique to perform unsupervised clustering, and contextual information is incorporated in the energy model. Initialized with a classification map based on Cloude-Pottier decomposition theory and K-Wishart distribution hypothesis, the classifiers and labels are updated by alternately solving a softmax regression problem and an MRF combinatorial optimization problem. The optimization process is iteratively executed until the termination criterion is met. We apply the proposed method on one real PolSAR data. Comparing with several other state-of-the-art algorithms, higher accuracies and better connectivity are achieved by the proposed method.

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TABLE I
FEATURES EMPLOYED IN DISCRIMINATIVE CLUSTERING METHOD

Polarimetric Feature category	Designation	Physical Description
Polarimetric matrices and mathematical transforms	$T_{ij}(i,j=1,2,3,i \leq j)$	Elements of coherency matrix under horizontal and vertical linear polarization way (modulus and argument)
	$Lin45T_{ij}(i,j=1,2,3,i \leq j)$	Elements of coherency matrix under $+45°$/-45° linear polarization way (modulus and argument)
	$CirT_{ij}(i,j=1,2,3,i \leq j)$	Elements of coherency matrix under left and right circular polarization way (modulus and argument)
	$\frac{I_{hv}}{I_{hh}}, \frac{I_{hv}}{I_{vv}}, \frac{I_{hh}}{I_{vv}}, \frac{I_{rr}}{I_{lr}}, \frac{I_{ll}}{I_{lr}}, \frac{I_{ll}}{I_{rr}}, \frac{I_{mn}}{I_{mm}}, \frac{I_{mn}}{I_{nn}}, \frac{I_{mm}}{I_{nn}}$	Intensities ratios under horizontal and vertical linear, $+45°$/-45° linear, and left and right circular polarization ways
	SPAN	Polarimetric total power
Target decomposition features	Pauli matrix components	Pauli decomposition parameters
	P_s, P_d, P_v, α_L	Freeman decomposition parameters
	$\bar{\alpha}, H, A, \beta, (1-H)(1-A), (1-H)A, H(1-A), HA$	Cloude-Pottier decomposition parameters

TABLE II
CA VALUES (%) OF FLEVOLAND AREA DATA WITH DIFFERENT METHODS

Method/Class	Bare soil	Barley	Lucerne	Peas	Potatoes	Beet	Wheat	*overall CA* value
$H/\bar{\alpha}$-Wishart classifier	99.94	86.60	84.63	88.50	81.44	84.00	82.48	85.59
Wishar MRF classifier	**100.00**	86.23	93.27	94.24	85.55	89.54	92.55	91.82
Freeman Wishart classifier	98.26	87.97	83.38	93.22	98.13	92.20	84.53	90.16
Power Entropy and Copolarized Ratio classifier	99.44	89.85	75.22	85.92	85.79	91.01	87.89	88.30
Wishart TMF classifier	99.81	97.60	86.10	**98.27**	90.00	95.86	97.33	95.86
The proposed method	**100.00**	**100.00**	**95.07**	98.21	**98.57**	**98.63**	**99.93**	**99.05**

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