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A New Classification Approach for PolSAR Images

T. J. Singh Chugh[1], R. B. Dubey[2] and Sujata[3]
ECE dept., SGI, Samelakha, Panipat, India[1], ECE dept., Hindu College of Engineering, Sonepat, India[2]
EE Department, DCRUST, Murthal, Sonepat, India[3]

Abstract

PolSAR images provide more information than the conventional radar images and so greatly improves the ability to terrain discrimination. This work is focused on the problem of the classification of different terrain types of PolSAR images. The proposed method uses a combination of two different classifiers. This method is named as Meta classifier and compared with other competitive classifiers. One as a spatial partitioning method, assigning each leaf of tree a distinct region label. So they are called as clustering trees. The other one is used as the second classifier for generating the class labels. But the final result is generated by voting over the ensemble results of the two classifiers. The experimental results obtained so far, indicate the potential of this approach.

Keywords

Feature evaluation, feature selection, multifeature combination, SAR image classification

1. Introduction

Environmental monitoring, earth-resource mapping, and military systems require broad-area imaging at high resolutions. Many times the imagery must be acquired in inclement weather or during night as well as day. Synthetic Aperture Radar (SAR) provides such a capability. SAR systems take advantage of the long-range propagation characteristics of radar signals and the complex information processing capability of modern digital electronics to provide high resolution imagery. SAR complements photographic and other optical imaging capabilities because of the minimum constraints on time-of-day and atmospheric conditions and because of the unique responses of terrain and targets to radar frequencies. SAR is a radar technology that is used from satellite. It produces high resolution images of earth's surface by using special signal processing techniques. SAR has important role in gathering information about earth's surface because it can operate under all kinds of weather condition such as cloudy, hazy or dark.

T. Zou et al., classify the terrain by using polarimetric SAR imagery has been a very active research field over recent years [1]. Although lots of features have been proposed and many classifiers have been employed, there are few works on comparing these features and their combination with different classifiers. F. Moosmann et al., introduce three new contributions to the problems of image classification and image search [2]. B. Kalpana et al., given a choice of classifiers each performing differently on different datasets the best option to assume is an ensemble of classifiers [3]. J. S. Lee et al., propose a new method for unsupervised classification of terrain types and man-made objects using polarimetric SAR data [5]. This technique is a combination of the unsupervised classification based on polarimetric target decomposition and the maximum likelihood classifier based on the complex Wishart distribution for the polarimetric covariance matrix. J. S. Lee et al., introduce three new contributions to the problems of image classification and image search [4]. Y. Yamaguchi, et al., said that a four-component scattering model is proposed to decompose polarimetric SAR images [6]. A. Freeman said that two simple scattering mechanisms are fitted to polarimetric SAR observations of forests [7]. The rest of this paper is organized as follows: In Section 2, methodology and various classifiers are formulated. Section 3 deals with the results and discussion. Finally, the concluding remarks are given in Section 4.

2. Methodology

META classifier is a combination of ERCF and KNN classifiers. Polarimetric features are divided into two categories: one is the features based on the original data and its simple transform, and the other is based on target decomposition theorems. The first category features mainly include the sinclair scattering matrix, the covariance matrix, the coherence matrix, and several polarimetric parameters. When analyzing polarimetric SAR data, there are also a number of parameters that have useful physical interpretation such as amplitude of HH-VV correlation coefficient, HH-VV phase difference, copolarized ratio in dB,

cross-polarized ratio in dB, ratio HV/VV in dB, copolarization ratio, and depolarization ratio.

2.1 Classifiers

2.1.1Efficiently Randomized Clustering Forests (ERCF)

ERC forests consist of randomized decision trees which predict class labels c from visual descriptor vectors of local regions d = { f_1. . . f_D }, where f_i, i = 1 , . . ., D are elementary scalar features. We train the trees using a labeled training set L = {d_n, c_n}, (n= 1, . . ., N), where we assume that all descriptors sampled from a given image share the same label c. During a query, each local descriptor d sampled from the query image traverses each tree from the root down to a leaf. Each tree assigns a unique leaf index to the visual descriptor and not the descriptor label c associated with the leaf during training. Thus, for each descriptor d, the ERC-forest returns a set of leaf indices, one for each tree, corresponding to the associated visual descriptor. The trees are built recursively in a top down manner, as in algorithm. We start building each tree from the complete training set L_0 = L, which corresponds to the complete descriptor space R [24].

Algorithm: tree growing algorithm

Tree (L_t): {Create a (sub)tree from labeled training set L_t }

if stopsplitting (L_t) = true t**hen**
  return createLeafNode (L_t)
else
  tries=0
  repeat
tries ← tries + 1
select an attribute number randomly
select a threshold _t randomly
split Lt according to test T : {$f_{it} < Q_t$} and
Calculate score:
L_l ← {f ∈ Lt| $f_{it} < Q_t$ }

Lr ← {f ∈ L_t | $f_{ti} \geq Q_t$ }
score ← Sc (L,T)
  until (score ≥ S_{min}) or (tries ≥ T_{max})
  select i_t , Q_t that achieved highest score
  return create Decision Node (i_t, Q_t, Tree(L_1),Tree(L_r)
end if

At each node t, has two children l and r are created by choosing a Boolean test T_t that divides L_t into two disjoint subsets L_t = L_1 U L_r with L_1 ∩ L_r =0. Recursion continues with L_t and L_r until further subdivision is impossible: either all surviving training examples belong to the same class or all have identical values for all feature attributes. In the algorithm, this criteria is checked by the function stop splitting ( ).We use thresholds on elementary features as tests T_t = {$f_i \leq Q_t$} for some feature index it and threshold i_t. The tests are selected randomly as follows: A feature index it is chosen randomly, a threshold i_t is sampled randomly from a normal distribution and the resulting node is scored over the surviving points by using the Shannon entropy:

$$S_c(L,T) = \frac{2.I_{C,T}(L)}{H_C(L)+H_T(L)} \quad (1)$$

H_C denotes the entropy of the class distribution in L:

$$H_C(L) = -\sum_{c\in C}\frac{n_c}{n}\log_2\frac{n_c}{n} \quad (2)$$

Where n is the size of the current set L and n_c is the number of descriptor vectors in L belonging to class c. It is maximal when all of the n_c are equal. Similarly, the split entropy H_T is defined for the test T which splits the data into two partitions:

$$H_T(L) = -\sum_{p=1}^{2}\frac{n_p}{n}\log_2\frac{n_p}{n} \quad (3)$$

The maximum is again reached when the two partitions have equal size. Based on the entropy of a given set, the impurity of a test can be calculated by the mutual information $I_{C,T}$ of the split:

$$I_{C,T}(L) = H_C(L) - \sum_{p=1}^{2}\frac{n_p}{n}H_C(L_p) \quad (4)$$

The method of feature index selection and threshold selection is repeated until the score is higher than a fixed threshold S_{min} or until a fixed maximum number T_{max} of trials have been made. The test T_t that achieved the highest score is adopted and the recursion continues. The parameters ($S_{min,}$ T_{max}) control the strength and randomness of the generated trees. High values produce highly discriminant trees with little diversity, while S_{min} = 0 or T_{max} = 1 produce completely random trees [24]. In this way, we build the trees as classification trees but use them as clustering trees. One can also think about the test T as a hyper plane in the descriptor space R. Hence, a given test T_t divides the corresponding space R_t into two disjoint regions, R_t =R_l U R_r, with R_l ∩ R_t = 0. The split of the region, of course, then results in the split of the training set L_t [24].

2.1.2 k-Nearest neighbour (KNN)

A drawback of ERCF classifier which classifies data when all attributes of test data matches exactly with at least one instance of train data. In real life scenarios many test records will not be classified because they do not exactly match any of the training records. A more sophisticated approach, *k*-nearest neighbor (KNN) classification finds a group of *k* objects in the training set that are closest to the test object, and bases the assignment of a label on the

dominance of a particular class in this neighborhood. Once the nearest-neighbor list is obtained, the test object is classified based on the majority class of its nearest neighbours. Majority voting

$$y = argmax(c) = \sum I(c = y_i) \qquad (5)$$

where c is a class label, y_i is the class label for the i*th* nearest neighbors, and $I(\cdot)$ is an indicator function that returns the value 1 if its argument is true and 0 otherwise.

2.1.3. Proposed classifier

The proposed classifier is Meta classifier. Meta classifier focuses on predicting the right algorithm for a particular problem based on characteristics of the database. A classifier ensemble, consists of a set of n classifiers $C_1, \ldots C_n$ called base-level classifiers and a meta-level classifier CML that learns how to combine the predictions of the base-classifiers. The base-classifiers are generated by applying n different classification algorithms on a labelled dataset, the training set, TRAINSET = {(x_k , y_k)}, where x_k and y_k are the features and the class value for the k-th instance vector respectively. The individual predictions of the base-classifiers on a different labeled dataset TESTSET, are used to train the meta-classifier CML. The predictions of the base-classifiers on TESTSET are then transformed into a meta-level set of classification vectors. At runtime, CML combines the predictions PM(x) = { P_i (x), i = 1…n} of the n base classifiers on each new instance x, from the test data and decides upon the final class value y(x). The final predictions of the base-classifiers on x are transformed into a single vector representation, which is then classified by CML. In stacking we use multiple algorithms and combine their results. The output from the previous layer is passed as input to the next layer. The output of a decision tree and can be used as input for a neural network.

Here, we propose a two-step Meta classifier stack generalization for predicting accurate results. The first step pre-process and selects the features required for classification and the second step uses base classifiers and a meta learning algorithm to induce a meta classifier based on probability distribution of base level classifiers.

2.1.4 Automatic Feature Combination

Automatic selection and combining different feature types are always necessary when facing a large number of feature types. Since there may exist many relevant and redundant information between different feature types, we need to not only consider the classification accuracies of different feature types but also keep track of their correlations. In this section, we propose a metric-based feature combination to balance the feature dependence and classification accuracy. Given a feature type pool F_i(i = 1, 2, . . . ,N), the feature dependence of the ith feature type is defined as

$$Dep_i = \frac{N-1}{\sum_{j=1,j\neq i}^{N} corrcoef(\overrightarrow{P_i},\overrightarrow{P_j})} \qquad (6)$$

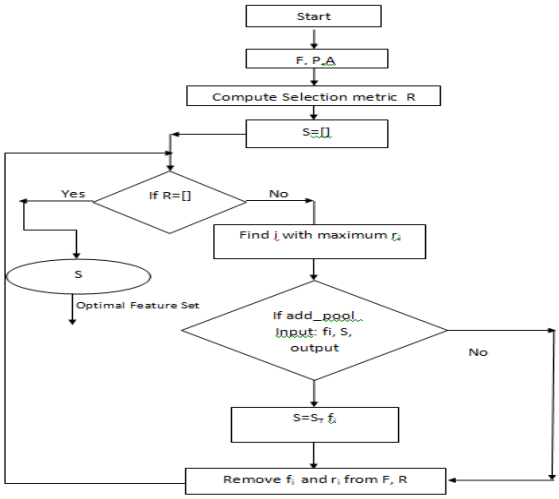


Fig.1: Flowchart to decide the multifeature combinations.

i is the terrain classification accuracy of the ith feature type in feature type pool. corrcoef (·) is the correlation coefficient. The Dep_i is actually the reciprocal of average cross correlation coefficient of the ith feature type, and it can represent the average coupling of the i^{th} feature type and the other feature types. We assume that these two metrics are independent as done in feature combination, and then the selection metric of the i^{th} feature type can be defined as

$$R_i = Dep_i . A_i \qquad (7)$$

where A_i is the average accuracy of the ith feature type. If the selection metric R_i is low, the corresponding feature type will be selected with low probability. While the selection metric R_i is high, it is more likely to be selected. After obtaining classification accuracy of each feature type, we propose to make feature combination by completely automatic combining method as flowchart from Fig.1. The features with higher selection metric have higher priority to be selected, and the feature is finally selected only if it can improve the classification accuracy based on the selected features with a predefined threshold.

Following the above mentioned three heuristic criterions and Table 2 we can obtain a combined feature set as {F1, F2, F4, F7, F9}, which is expected to get comparable performance than combination of all the features. It can be learned that the selected feature set gets a slightly higher average accuracy. We also find that the multifeatures combination can greatly improve the performance by 4 to 8%. When selecting three feature types in the first category and two feature types in the second category using the KNN classifier, we can get the same combination result as heuristic feature combination.

The features with higher selection metric have higher priority to be selected, and the feature is finally selected only if it can improve the classification accuracy based on the selected features with a predefined threshold. In the following experiment some intermediate feature combination states are selected to illustrate that the feature combination strategy can improve the classification performance step by step. The intermediate feature combination states include the following:
Pset1: select 1 feature type in the first category and 1 feature type in the second category; the combination features include F2 and F9.
Pset2: select 2 feature type in the first category and 1 feature type in the second category; the combination features include F1, F2 and F9.
Pset3: the final selected feature set {F1, F2, F4, F7, F9}.

3. Results and discussions

PolSARpro v.4.0 software is used for classification of various land features. The land features include ocean, clear water, settlements, agriculture fields, arid lands, grown and young forest, hilly terrain, mangrove forest, etc. The data acquired is processed by PolSARpro v4.0 software for classification of various land features. The software is freely available on the internet and is developed by ESA. The set of nine independent parameters of this particular parameterization allows a physical interpretation of the target. On the whole, the investigated typical polarimetric features include:

F1: amplitude of upper triangle matrix elements of S
F2: amplitude of upper triangle matrix elements of C
F3: amplitude of upper triangle matrix elements of T
F4: the polarization parameters
F5: the three parameters $|\alpha|^2$, $|\beta|^2$, $|\gamma|^2$ of the Pauli decomposition
F6: the three parameters ks, kd, kh of the Krogager decomposition
F7: the three scattering power components Ps, Pd, Pv of the Freeman-Durden decomposition;
F8: the three parameters H-α-A of the Cloude pottier decomposition
F9: the nine parameters of the Huynen Decomposition.

These features are shown in Fig. 2.

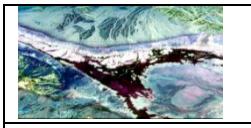


Fig. 2: PolSAR image extracted from the satellite data

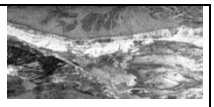


Fig. 2.1: Krogager_kd_db

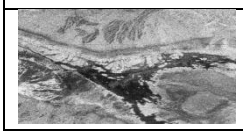


Fig. 2.2: Krogager_kh_d

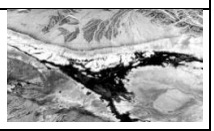


Fig. 2.3: krogager_ks_db

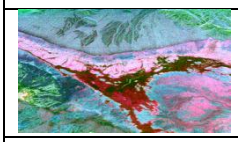


Fig. 2.4: Huynen_RGB

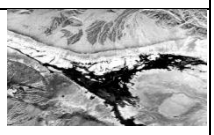


Fig. 2.5: Hyunen_T11_db

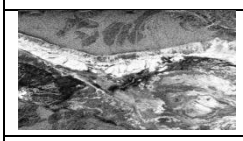


Fig. 2.6: Hyunen_T22_db

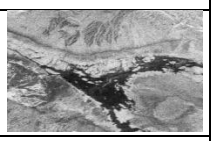


Fig. 2.7: Hyunen_T33_db

Fig. 2.8: Freeman_dbl_db

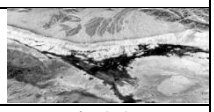


Fig.2.9: Freeman_odd_db

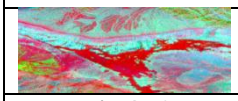


Fig. 2.10: Freeman_RGB

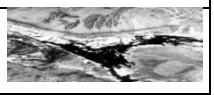


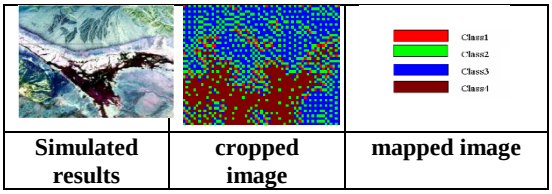
Fig. 2.11: Freeman_Vol_db

Fig. 2: Different Polarimetric features extracted with the help of PolSARpro.

Table 1: Classification accuracy of single polarimetric Descriptor using KNN & ERCF

Features	Classifiers	Class1	Class2	Class3	Class4	All Classes
F1	ERCF	68	39	63	81	68.75
	KNN	84	30	2	43	39.25
F2	ERCF	88	34	69	72	69.5
	KNN	99	20	4	0	30.75
F3	ERCF	69	41	67	76	63.85
	KNN	87	39	11	36	43.25
F4	ERCF	69	45	64	78	64
	KNN	86	28	0	84	49.5
F5	ERCF	66	43	65	86	65
	KNN	88	8	2	78	44
F6	ERCF	73	53	77	86	72.25
	KNN	90	23	5	93	52.75
F7	ERCF	53	36	49	47	46.25
	KNN	94	10	0	0	26
F8	ERCF	61	51	54	50	54
	KNN	41	54	56	73	56
F9	ERCF	69	36	54	48	31.75
	KNN	92	6	18	2	29.5

The SAR images are classified by using 3 different algorithms, namely ERCF, KNN and Meta algorithms. The performance of these three algorithms is compared using efficiency for given samples. The results showed that, among these three algorithms the META algorithm gives better classification results over the ERCF and KNN algorithms. The MATLAB simulation result will have very large no of values. So, the region of interest (ROI) is cropped from the MATLAB simulation result. The cropped image is mapped into for labels: red, green, blue and dark red as shown in Fig. 3.



Simulated results	cropped image	mapped image

Fig. 3: Simulation results.

Table 2: Set of Multifeature combinations

S. No.	Threshold (T)	Optimal Feature	Features in Set
1	4	Pset1	F2 , F9
2	3	Pset2	F1, F2 , F9
3	2	Pset3	F1, F2,F4,F7,F9

Table 3: Performance of different classifiers.

Feature sets	Average classification accuracy		
	ERCF (%)	KNN (%)	META (%)
Complete	52.5	52.5	66-79
Single	46-72	26-56	63-76
Multiple	64-70	53-61	69-80

This table shows the optimal multiple feature set that has been selected with multifeature combination algorithm. Threshold shows the improvement in percentage accuracy that must be achieved for adding the single polarimetric feature to optimal feature set.

Table 4: Comparison of KNN, ERCF, META efficiency

Feature	Efficiency in terms of samples		
	ERCF	KNN	META
F1	70	68.8	76.8
F2	68	71.6	76.8
F3	59.2	70.8	65.6
F4	70.8	58.4	78.8
F5	63.6	65.6	66.4
F6	62.4	64.8	76.8
F7	70.4	68.8	76.4
F8	71.2	68.4	79.2
F9	68.4	68.8	74.4
F10	70	70.4	65.6
F11	69.6	70.4	74.8
F12	63.6	71.2	69.6

4. Conclusions

Proposed method named as META (combination of ERCF & KNN) uses the extremely randomized trees as spatial portioning method at the base for cluster formation. Then KNN is used at cluster level for assigning the class labels. Final classification map is generated by voting over the ensemble of trees. The classification accuracy has been improved compared to the other competitive classifiers. The results

reveal that with the single feature dimension there is large variance in the classification accuracy among different classes with each classifier. Multifeature combination results in variance reduction. The META is a promising approach for POLSAR image classification and deserves the particular attention towards its use. In future, we will focus our attention towards more features such as texture; shape etc. to perform more efficient feature selection.

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Rash Bihari Dubey was born in India on 10th November 1961. He received the M. Sc. degree in Physics with specialization in Electronics in 1984 from Agra University Agra, India, the M. Tech. degree in Instrumentation from R.E.C. Kurukshetra, India in 1989 and the Ph.D. degree in Electronics Enggg., from M. D. University, Rohtak, India in 2011. He is at present Professor and Head in the Department of Electronics and Communication Engineering at Hindu College of Engineering, Sonepat, India. He has well over 40 publications in both conferences and journals to his credit. His research interest are in the areas of Medical Imaging, Digital Signal Processing, Digital Image Processing, Biomedical Signal Analysis, and Industrial Real Time Applications.

Tarun Jeet Singh Chugh was born on 14th July 1987. He received his B.E. degree in Electronics and Communication Engineering from M. D. U., Rohtak in 2009 and M. Tech. Degree in Electronics and Communication Engineering from M. D. U., Rohtak. Currently he is working as a lecturer in the Department of Electronics and Communication Engineering, SGI, Samelakha, Panipat, Haryana, India.

Sujata Bhatia was born on 21st October 1987. She received her B. Tec. degree in biomedical engineering from Guru Jambheswer University of science and technology, India 2010 and pursuing M. Tech. in Instrumentation and Control from DCRUST, Murthal, Sonepat, India.