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Optimum Ensemble Classification for Fully Polarimetric Synthetic Aperture Radar Data Using Global-local Classification Approach

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ABSTRACT

In this paper, a ensemble classification for fully polarimetric synthetic aperture radar (PolSAR) data using a global-local classification approach is discussed. In the first step, to perform the global classification, the training feature space is divided into a specified number of clusters. In the next step local classification over each of these clusters is conducted; which contains elements of several classes, a base classifier. Thus, an ensemble of classifiers was formed; each of them professionally acts as a part of the feature space. To achieve more diversity, the data set is independently partitioned into a variable number of clusters by H/α classifier and K-means algorithm. To combine the outputs of different arrangements, majority voting, Naïve Bayes and a heuristic combination rule by taking into account the classification accuracy and reliability (which in PolSAR classification less attention has been paid to it) as objective functions were used. The experimental results over two PolSAR images preved effectiveness of the proposed algorithms in compare to baseline methods.

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NOMENCLATURE

S	scattering matrix	DERD	double-bounce eigenvalues relative difference
HH, HV, VH and VV	scattering matrix elements	SERD	single-bounce eigenvalues relative difference
T	coherency matrix	d_m	Wishart distance
C	covariance matrix	k_d	diplane parameter of Krogager decomposition
C_m	mean covariance matrix	H	Entropy of Cloude-Pottier decomposition
		A	mean alpha angle of Cloude-Pottier decomposition

1. INTRODUCTION

Synthetic aperture radar (SAR) is an imaging radar technique which can produce high-resolution images of the earth's surface by signal processing of the recorded radar echoes. Since SAR is an active sensor and uses longer microwave wavelengths, it is largely independent of weather conditions and has a day-and-night imaging capability [1].

A polarimetric SAR (PolSAR) system, which works in quad- (full) polarization mode (generates quad-polarized data consisting of four linear polarizations, namely, HH, HV, VH and VV), provides significantly more information than single and dual synthetic aperture radar systems. Using the measured data, which are in form of a complex scattering matrix, the fine configuration, orientation, geometric structure, and physical information of targets can be identified [2].

Classification of polarimetric SAR data has received considerable attention during the past decade. In addition, many algorithms for the supervised and unsupervised classification have been developed. According to recent research outcome, ensemble of classifiers as an effective approach has more capabilities, as compared to single classifiers [3]. The idea of ensemble learning methods is to build an improved model by integrating decisions of multiple classifiers. Firstly, several different weak individual classifiers are generated; then, they are weighted and a better classifier is obtained by combining their

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predictions. Given the same amount of information, an ensemble decision can often be better than the decision from any single classifier [4].

In spite of the considerable amount of work that has been carried out on the use of an ensemble of classifiers in recent years; only a few applications have been reported for PolSAR data. As literature reported [5], a soft voting strategy is utilized to fuse multiple base classifiers. In this method, which is based on majority voting, when base classifiers have different opinions in the voting system, the support vector machine (SVM) classifier can be considered as the decider [6]. Compared with base classifiers, the proposed algorithm was found to be more accurate. In the next step, classification maps were provided with more homogeneous regions by integrating the spatial information. In order to create a classifier ensemble, several networks of binary classifiers (NBCs) are used to discriminate each class label and perform evolutionary search to find the optimal BC in each NBC [7]. An ensemble of SVM classifiers was proposed in literature [8]. In this scheme, each classifier has its own feature selection component and is trained on an individual class. They demonstrated that this system significantly improves classification accuracy over a single-classifier system.

In conventional methods that use a single classifier, all samples, which have been distributed in the feature space, are distinguished by only one classifier. In these approaches, the recognition of samples of several classes that are close to each other is a challenging process. To overcome this drawback, a proposed ensemble of classifiers is presented. In the proposed algorithm, we used the idea of global and local classifications to cluster the feature space and form an ensemble of classifiers. One of the main components of ensemble classifiers is diversity among base classifiers which can be achieved by frequent data set clustering. Decisions from different clustering arrangements are combined using majority voting, Naïve Bayes rule and a proposed multi objective optimization algorithm. Besides the classification accuracy, reliability parameter that shows the validity of a final decision in the face of a new pattern is particularly important. However, little attention has been paid to reliability in designing ensembles of classifiers, especially for polarimetric images. Therefore, using a multi objective optimization algorithm and considering classification accuracy and reliability as objective functions, a structure is proposed for an optimized ensemble of classifiers.

The rest of this paper is structured as follows. Section 2 introduces PolSAR data, ensemble of classifier, multi-objective optimization algorithms and baseline methods. In section 3, the proposed algorithms are explained. Finally, data set and the experimental results are described and discussed in section 4.

2. METHODLOGY

2. 1. Polarimetric SAR Data

Polarimetric radars measure the amplitude and phase of backscattering signals in four linear polarizations: 1) HH; 2) HV; 3) VH; and 4) VV. These signals form a complex scattering matrix S, which relates the incident and the scattered electric fields. In order to best extract physical information from the scattering matrix, coherency matrix [T] and covariance matrix [C] can be constructed [9]. There is a variety of polarimetric parameters which can be extracted from polarimetric SAR data. These parameters are divided into three categories: 1) the features directly obtained from original data, e.g., the scattering matrix, the covariance matrix, or the coherency matrix, 2) the features which are derived using well-known decomposition methods (e.g., Krogager, Freeman) and 3) the SAR discriminators [8].

Cloude and Pottier decomposition (which is one of the most used approaches) defines several parameters (entropy, anisotropy, and alpha angle) based on eigenvalues and eigenvectors of averaged coherency matrix. Entropy and anisotropy are used to characterize media's scattering heterogeneity, and alpha is the measurement of the type of scattering mechanisms from surface, to dipole, and to double bounce [10].

2. 2. Ensemble of Classifiers

The results of previously conducted studies show that the system performance could be improved by integrating decisions of multiple classifiers. This structure often appears in the literature under many creative names such as composite classifier systems, mixture of experts, the combination of multiple classifiers, classifier fusion, committees of neural networks, voting pool of classifiers, classifier ensembles, etc. [11]. We need classifiers whose decision boundaries are adequately different from those of others. Such a set of classifiers is said to be diverse. In other words, diversity is obtained when misclassification events of base classifiers are not correlated. In general, three major approaches for generating a diverse ensemble of classifiers are offered [12]. The first approach to achieve diversity is to use different training data sets to train individual classifiers. These datasets are drawn randomly, usually with replacement, from the entire training data. Bagging and boosting are the most important methods in this approach. In the second approach, diversity is obtained by using different features for training base classifiers. Finally, diversity can also be achieved using different training parameters for different classifiers. In this paper, for generating diverse base classifiers, we proposed a method based on the first approach which uses data clustering.

For combination rule, different methods including weighting methods, majority voting, Bayesian combination, entropy weighting and Naïve Bayes are introduced [13]. In this paper, to combine outputs of base classifiers, we used majority voting, Naïve Bayes rule and a proposed evolutionary method, which makes use of multi-objective optimization techniques [14].

Since polarimetric data have intrinsic physical meaning, no prior information is required about the scene for classification. Thus, it is an ideal data for the unsupervised classification. H/α classifier is one of the most well-known unsupervised classifications which has been applied to polarimetric data. In this method, using target entropy and alpha angle, a two dimensional feature space is formed, which is then subdivided into nine possible categories [15].

2. 3. Multi-objective Optimization Methods

In some problems, we need to optimize several objectives simultaneously. An optimization problem with M objectives and restrictive conditions is defined as Equation (1):

$$\begin{aligned} &Minimize\ \ f(x)=[f_i(x), i=1,2,\ldots,M] \\ &g_j \le 0 \quad j=1,2,\ldots,J \\ &h_k = 0 \quad k=1,2,\ldots,K \end{aligned} \tag{1}$$

where, $f_i(x)$ is the objective function, $g_j(x)$ is the restrictive condition as inequality and $h_k(x)$ is the restrictive condition as equality. Objectives are often in conflict with each other in such a way that the optimal solution for one is a non-optimal solution for the rest. In such a situation, we should do a reasonable compromise between solutions and select a solution which is mostly optimal for all the objectives. One of the fundamental concepts of the multi-objective problem is the concept of domination. Solution x_1 dominates x_2 if:

$$\begin{aligned} &1.\ f_i(x_1) \le f_i(x_2) \ \ \textit{for all } i=1,2,\ldots,M \\ &2.\ f_i(x_1) \prec f_i(x_2) \ \ \textit{for at least one index } i=1,2,\ldots,M \end{aligned} \tag{2}$$

If U is the set of all solution, $x_i \in U$ is called Pareto optimal if and only if there is no $x_j \in U$ which dominates it. The set of Pareto optimal outcomes is often called Pareto front or Pareto boundary. Several methods such as NSGA I and II [16] also multi-objective particle swarm optimization (MOPSO) [17] are introduced to generate Pareto optimal. In this paper, the MOPSO method is used.

In this study, we have used the classification accuracy and reliability as objective functions. Classification accuracy for a class is defined as the ratio between number of samples in a class which are correctly classified and all samples in that class. According to this definition, the fitness function for optimizing the classification accuracy of classifier Di can be introduced by Equation (3):

$$fit_1(D_i)=(T_i - Miss(D_i))/T_i \tag{3}$$

where, T_i is the total number of samples and Miss (D_i) is the number of samples incorrectly classified by classifier D_i.

Reliability as an important criterion in pattern processing shows the validity of a final decision in the face of a new pattern. A classifier has often the ability to recognize all patterns of a particular class; however, its reliability is reduced due to entry of samples of another class. Reliability of class I (R_i) is defined as the ratio between the number of samples of this class which are correctly recognized (H_i) and the total number of samples assigned to this class (H):

$$R_i = H_i / H \tag{4}$$

Therefore, based on the reliability criterion, the fitness function for classifier D_i is defined as Equation (5):

$$fit_2(D_i)=\prod_{j=1}^{M} H_j \tag{5}$$

2. 4. Baseline Methods

We compared the proposed algorithms with two baselines classifiers, namely neural network and Wishart classifier. The Wishart classifier proposed by Lee et al. [18] is one of the most widely used methods for the classification of polarimetric data. It has been shown that the polarimetric covariance matrix Z may be described by a complex multivariate Wishart distribution. The Wishart distance measure based on the maximum likelihood classifier and the complex Wishart distribution is derived by Equation (6):

$$d_m = \ln|C_m| + Tr(C_m^{-1}Z) \tag{6}$$

where, $C_m=E[Z|\omega_m]$ is the mean covariance matrix for class ω_m . For the supervised classification, C_m is estimated for each class using training sets. To classify a pixel, it is assigned to class ω_i, $i\in\{1;2;\ldots;k\}$ if:

$$d_m^{(i)} \le d_m^{(j)} \quad \forall \omega_i \ne \omega_j \tag{7}$$

3. PROPOSED MODEL

When we use only one classifier, it is likely that samples of all areas of the feature space will not be correctly classified. A solution to this problem is to cluster the feature space into several clusters and use individual classifiers for each cluster and finally, combine results with each other [19]. In this way, we trained a set of base classifiers, each of which professionally acts on a part of the feature space. To classify a test sample, we firstly determine the relevant cluster and then, used the corresponding trained classifier, specify its class label. In other words, classification of a test samples takes place in two stages of global and local classifications. With clustering, global classification process is performed over the entire feature space for finding the approximate position of the test sample. Next, using the corresponding classifier, local classification is performed to determine the exact class label.

If this issue is viewed from the perspective of ensemble classification, instead of using one classifier, several efficient classifiers are used, each of which precisely classifies a part of the feature space.

For increasing diversity, the clustering process is repeated and the feature space is clustered with different arrangements, and base classifiers are also trained over clusters of each arrangement. In this paper, the unsupervised classifiers H/α and k-means algorithm were used to generate various clustering schemes.

To determine the class label of a test sample, at first, the corresponding cluster is defined for each of clustering arrangements and then, a class label is produced using the relevant classifier. In the final step, the decisions obtained from various clustering schemes are fused into a final class label. In this paper, the decisions of individual clustering arrangements are fused using majority voting, Naïve Bayes and a multi-objective heuristic combination rule. The detail of the proposed algorithm is as follows:

In the first step, the training and test sets are formed. Figure 1 represents this process. Firstly, while surveying overall display of the image, a desired area is selected using PolSARpro software, and the coherency matrix of the pixels in this area is extracted. Depending on the land cover of the selected area, C classes are considered. The problem of speckle as one of the main issues in polarimetric SAR data complicates the image analysis and reduces the effectiveness of image segmentation and classification [20]. Thus, the speckle reduction is a fundamental step prior to extracting valuable parameters of PolSAR data. Several methods such as Multi-look processing, Lee filter, refined Lee filter and IDAN filter have been proposed to reduce speckle [21]. These methods attempt to find a good compromise between speckle reduction and preservation of spatial details.

Coherent parameters must be extracted prior to the speckle reduction process [8]. Therefore, incoherent parameters are extracted from a coherent matrix, which is filtered by one of the speckle reduction methods, and coherent parameters are extracted from a non-filtered coherent matrix.

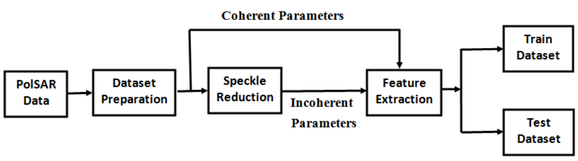

Figure 1. The process of training and test sets forming

As mentioned in previous section, a large number of parameters can be extracted from PolSAR images. Using all these features increases the system complexity as some of them are likely to carry redundant information. Finally, among the various features, nine optimum parameters which have been widely used in literature were selected [8, 22]. These parameters are listed in **Error! Reference source not found.**. The depolarization ratio describes how completely a target depolarizes incident polarized signal [8].

The proposed scheme for the training process can be seen in Figure 2(a). In this scheme, N arrangements (clustering scheme) are used. The first arrangement contains n_1 clusters, the second arrangement, which uses H/α classifier as the clustering algorithm, consists of nine clusters, and Nth arrangement contains n_N clusters. The process of training is as follows: for each clustering scheme, the training data set is partitioned into corresponding number of clusters. In this case, for each cluster, two different modes may occur, that is the cluster contains samples of only one class or several classes. For each cluster containing samples of multiple classes, an independent base classifier is trained.

The process of classifying a test sample can be seen in Figure 2(b). At the first stage, for each of the arrangements, a corresponding cluster is determined. If a base classifier is trained over that cluster, class label of the sample is determined using that classifier; otherwise, class label of samples of that cluster is assigned to the test sample. Finally, the outputs of arrangements are combined by the majority voting or by Naïve Bayes rule.

3. 1. Multi-objective Optimization

In the next proposed method, using multi-objective optimization algorithms, weights of each arrangement will be defined. Therefore, the classification accuracy and reliability as the two objective functions of the final classifier ensemble are simultaneously maximized.

TABLE 1. Polarimetric parameters used in this study

	Symbol	Description
1	k_d	diplane parameter of Krogager decomposition
2	DERD	double-bounce eigenvalues relative difference
3	SERD	single-bounce eigenvalues relative difference
4	H	Entropy of Cloude-Pottier decomposition
5	Alpha	mean alpha angle of Cloude-Pottier decomposition
6	S_{vv}	Scattering matrix element
7	C_{23}	Covariance matrix element
8	T_{22}	Coherency matrix element
9	dep_ind	Depolarization ratio

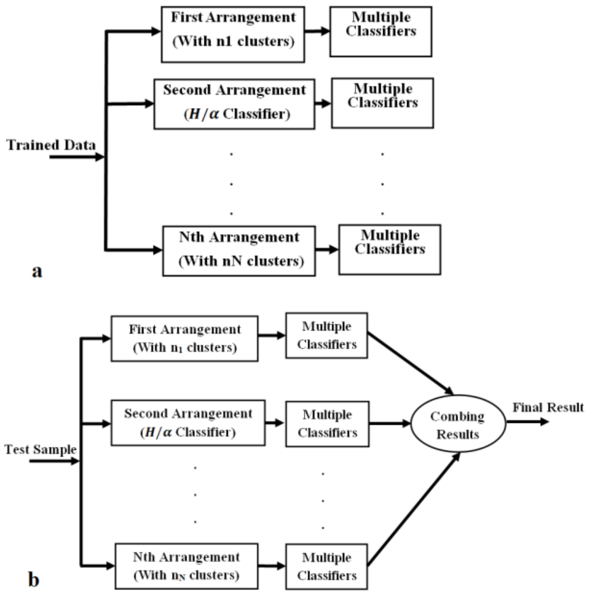

Figure 2. (a) The proposed scheme for the training process and (b) The process of classifying a test sample

The remarkable point in this proposed method is that the reliability parameter as an objective function is considered to design an optimal classifier ensemble which is an innovative aspect in PolSAR data. The proposed scheme is shown in Figure 3.

Steps of data preparation, speckle reduction, feature extraction and training and test data set forming are performed as in the previous section. The majority voting rule considers equal weights for all arrangements. However, in this scheme, we try to generate optimum output with effective weighting of arrangements. For this purpose, a weighting vector [23] is defined. In this scheme, the coefficient w_{ij} represents the weight of arrangements i with output of class label jj. Given the weighting vector and according to the output of each arrangement, the corresponding weights are extracted and the weights of the same class label are added together. Finally, the class with the maximum summation is declared as the output of the ensemble of classifiers.

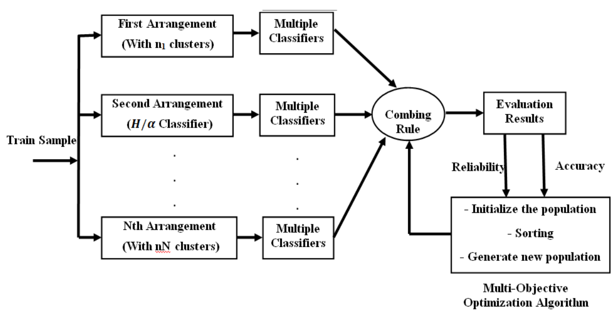

Figure 3. The process of training and test sets forming

In this proposed method, the training data set is divided into two subsets. The first subset is used for clustering data and training the base classifiers. The second subset is used for determining the optimum w_{ij} weights. Heuristic multi-objective optimization algorithms with objective functions of classification accuracy and reliability are used to determine the optimal w_{ij} weights. Finally, using test data set, the performance of the proposed classifier ensemble can be assessed.

4. EXPRIMENTAL RESULTS

To assess the proposed algorithms, we selected two PolSAR images from an airborne system (NASA/Jet Propulsion Laboratory AIRSAR) and a spaceborne system (Canadian Space Agency RADARSAT-2). AIRSAR supports polarimetric modes for C, L, and P-bands where we focus on L-band and RADARSAT-2 working in C-band also supports the full polarimetric mode. The two selected PolSAR images are from two different areas, including Flevoland, Netherlands, and the San Francisco Bay Area (SF Bay), California, USA. There are 15 ground-truth classes in the AIRSAR image. The Pauli-coded pseudocolor image and the used ground truth data are shown in Figure 4(a). The other image contains five classes, including water and vegetation along with developed, high, and low-density urban areas. The Pauli color-coded image and the ground truth data are shown in Figure 4(b). This setup demonstrates how effective the proposed algorithms are over a variety of PolSAR images in terms of the system (AIRSAR and RADARSAT-2), the operative band (C and L), and the underlying classification problem (e.g., number of classes and terrain types).

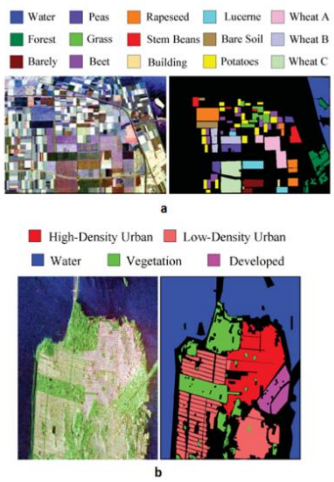

Figure 4. (a)AIRSAR L-band Flevoland, Pauli color-coded image and used ground truth. (b) RADARSAT-2 San Francisco 2008 C-band, Pauli color-coded image C-band and used ground truth. Class legend for ground truth on top [24]

Using the ground truth, the training and testing sets for each PolSAR image are generated as follows: the training and testing samples were randomly chosen with a training-to-testing ratio of 1:2. For the training set, we select ∼150 pixels/class for the AIRSAR image and ∼300 pixels/class for the RADARSAT-2 image.

In the first step, processes of preparing data, speckle reduction and feature extraction, which are the same for all the algorithms, are performed. Based on the capabilities of the refined Lee filter to preserve the polarimetric properties and the statistical correlations between channels [5]. We used this filter for speckle reduction with a 5 × 5 window. For each training and testing sample, according to **Error! Reference source not found.**, the feature vector of length 9 is formed. In the following, the training data are clustered with multiple arrangements. To do this, the unsupervised H/α classifier (with nine clusters) is used for one arrangement and the K-means algorithm with various clusters is used for the other arrangements. Then, for each cluster whose samples belong to more than one class, an SVM classifier is trained. These SVM classifiers use Gaussian radial basis function as kernel and OAO approaches to produce multiclass classification.

In the first proposed algorithm, the majority voting and Naïve Bayes rules are used for combining the results. In the second proposed algorithm, a heuristic combination rule whose weights are given by the MOPSO method is utilized for fusing the outputs (Figure 3). In this case, the classification accuracy and reliability are considered as objective functions.

In the following, to evaluate the performance of the proposed methods, their results have been compared with those of the baseline methods. For this purpose, the Wishart classifier and the neural network have been chosen as the base methods. In this scheme, a perceptron neural network with one hidden layer is used as one of the base classifiers. The number of neurons in the input layer is set to the number of features while the output layer consists of one neuron representing the class label. Five neurons are also considered for the hidden layer. In the following, more analysis with evaluation results will be presented for each of the individual PolSAR image.

4. 1. Experiment Using AIRSAR Image As expressed in previous section, this image consists of a large number of classes (15 classes), majority of which are agriculture fields. In the first step, the training data are clustered with five different arrangements (one with the unsupervised classifier H/α (with nine clusters) and the rest with K-means algorithm with 1, 2, 4 and 8 clusters). Then, individual SVM classifiers are trained over each cluster whose samples belong to more than one class. For determining the class label of a test sample, at first, the corresponding cluster (among the five clustering arrangements) is defined and then, a class label is produced using the trained classifier over that cluster. Therefore, for each test sample, there are five verdicts that should be combined to generate the final verdict. Various verdicts can be fused by the majority voting, Naïve Bayes or the heuristic combination rule.

In the case of the heuristic combination rule the lower and upper values for the weights are considered to be 0.1 and 100, respectively. MOPSO is run with a population of 500 particles and maximum iteration of 150. Parameters c_1, c_2 and w are set as 1, 2 and 0.5, respectively. After running MOPSO, a set of non-dominated answers are achieved. In this paper, among the non-dominated answers, the one with the best classification accuracy is chosen as the optimum weight vector. Using this optimum weight vector, the results are combined.

The results of comparing the performance of the proposed schemes (using majority voting, Naïve Bayes and the heuristic combination rules) with the baseline methods are given in **Error! Reference source not found.**.

4. 2. Experiment Using RADARSAT-2 Image This data includes a good coverage of both natural and man-made targets and contains five classes. To evaluate the first proposed algorithm, the training data are clustered using four different clustering arrangements. The unsupervised classifier H/α (with nine clusters) and the K-means algorithm with 1, 2 and 4 clusters are used for the clustering arrangements. Then, individual SVM classifiers are trained over each cluster. Using this ensemble of classifiers, test samples are classified.

In the next step, the optimum weight vector is determined using the MOPSO algorithm. The setting for the MOPSO algorithm is as follows: c_1, c_2 and w are set at 1, 2 and 0.5, respectively. The population size and the maximum iteration are considered to be 300 and 100, respectively. Moreover, the lower and upper values for the weights are set to 0.1 and 100, respectively.

Among the non-dominated answers which are provided by the MOPSO algorithm, the one with the best classification accuracy is chosen as the optimum weight vector. Using this optimum weight vector, the results from different arrangements are combined.

The classification accuracies of different arrangements for various classes are shown in Figure 6(b). In this case, like the previous image, each arrangement has better performance for some classes compared to other arrangements. For example, H/α classifier for class high-density and the arrangement with four clusters for classes vegetation and low-density have better performance. So, these arrangements also form a diverse ensemble of classifiers. Comparative results of the proposed algorithms with the baseline algorithms in terms of classification accuracy and reliability are shown in **Error! Reference source not found.**.

TABLE 2. The results of comparing the performance of the proposed schemes with the baseline methods for AIRSAR Image

	Accuracy	Reliability
Wishart	66.83	17e-4
Neural network	61.03	4.37
Proposed method in [5]	62.23	5.41
Proposed method in [23]	66.76	9.58
proposed scheme with majority voting	89.16	16.44
proposed schemewith Naïve Bayes	89.25	16.73
proposed scheme with heuristic combination rule	90.02	19.38

TABLE 3. The results of comparing the performance of the proposed schemes with the baseline methods for RADARSAT-2 Image

	Accuracy	Reliability
Wishart	70.90	19.39
Neural network	78.33	29.51
Proposed method in [5]	82.17	32.88
Proposed method in [23]	79.25	33.58
proposed scheme with majority voting	82.95	38.98
proposed schemewith Naïve Bayes	83.10	38.78
proposed scheme with heuristic combination rule	83.46	39.65

5. CONCLUSION

In this article, we proposed an ensemble of classifiers for the PolSAR data classification. In this scheme, using global and local classification strategies, the feature space was clustered several times with various arrangements and individual base classifiers were trained over clusters of each arrangement. In the next step, the decisions from different arrangements were merged into a final verdict. The majority voting, Naïve bayes, and a proposed multi-objective heuristic combination rule were used to combine the decisions. The proposed combination rule used classification accuracy and reliability as objective functions. To evaluate the effectiveness of the proposed algorithms, we considered nine efficient PolSAR features over two PolSAR images from the AIRSAR and RADARSAT-2 systems and compared the results with the baseline classifiers, including the Wishart classifier and the neural network.

In this paper, using the idea of clustering the search space and training individual classifiers over each cluster, an ensemble of efficient base classifiers was created. In this way, each of the base classifiers professionally operated in an area of the feature space, and the combination of their decisions resulted in increasing the efficiency of the system. Moreover, to raise diversity (which is one the most important components of an ensemble of classifiers), a multiple clustering technique was used. In addition to the K-means algorithm which is a popular algorithm for data clustering, the unsupervised H/α classifier as a specialized clustering algorithm was also used for PolSAR data. Another innovative aspect of this paper was using the parameter of reliability as one of the objective functions to design the heuristic combination rule for the PolSAR data classification ensemble.

We observed that the first proposed method (using majority voting) improved the average performance of baseline methods in terms of accuracy and reliability with averages of 16.78 and 14.38%, respectively. Furthermore, the second proposed method, which used an innovative combination rule, was observed to increase the efficiency of the system, especially in terms of reliability, by 16.2%. The experimental results also demonstrated that the use of multiple clustering arrangements for enhancing diversity resulted in more efficient ensemble of classifiers. However, the excessive increase in the number of these arrangements may be insignificant or lead to a decline in the system performance. Moreover, as reliability is intended as one of the selection criteria to optimize the ensemble of classifiers, the final decision is more valid.

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Optimum Ensemble Classification for Fully Polarimetric Synthetic Aperture Radar Data Using Global-local Classification Approach

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چکیده

در این مقاله، ساختار یک طبقه‌بند شورایی با استفاده از رویکرد طبقه‌بندی عمومی–محلی برای داده‌های پلاریمتریک رادار با روزنه مصنوعی پیشنهاد می‌شود. در گام نخست برای اجرای طبقه‌بندی عمومی، فضای ویژگی داده‌های آموزش به چندین خوشه تقسیم‌بندی می‌شود. در گام بعدی برای انجام طبقه‌بندی محلی بر روی هر یک از خوشه‌ها که شامل عناصر چند کلاس است، یک طبقه‌بند پایه آموزش داده می‌شود. به این ترتیب شورایی از طبقه‌بندهای پایه که هر یک بر روی ناحیه‌ای از فضای ویژگی به صورت تخصصی عمل می‌کنند، تشکیل می‌شود. جهت دستیابی به گوناگونی بیشتر، مجموعه داده به صورت مستقل توسط طبقه‌بند H/α و الگوریتم K-means به تعداد متغییری خوشه تقسیم می‌شود. جهت تلفیق خروجی آرایش‌های مختلف از رای‌گیری اکثریت، روش Naïve Bayes و یک قاعده ترکیب ابتکاری با در نظر گرفتن دقت طبقه‌بندی و قابلیت اطمینان(که در مباحث طبقه‌بندی تصاویر پلاریمتریک کمتر به آن توجه شده است) استفاده گردیده است. نتایج تجربی بیانگر برتری الگوریتم‌های پیشنهادی در مقایسه با روش‌های پایه است.

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