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Polarimetric SAR Images Classification using Collective Network of Binary Classifiers

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Abstract— **In this paper, we propose the application of collective network of (evolutionary) binary classifiers (CNBC) to address the problems of feature/class scalability and classifier evolution, to achieve a high classification performance over full polarimetric SAR images even though the training (ground truth) data may not be entirely accurate. The CNBC basically adopts a "Divide and Conquer" type approach by allocating an individual network of binary classifiers (NBCs) to discriminate each SAR image class and performing evolutionary search to find the optimal binary classifier (BC) in each NBC. Such design further allows dynamic class and SAR image feature scalability in such a way that the CNBC can gradually adapt itself to new features and classes with minimal effort. Experiments demonstrate the classification accuracy and efficiency of the proposed system over the fully polarimetric AIRSAR San Francisco Bay data set.**

I. INTRODUCTION

The accurate classification of polarimetric synthetic aperture radar (SAR) images is a major and challenging task. Supervised classification techniques such as artificial neural networks (ANNs) [1], [3], and [11] have proven to perform well for classification of polarimetric SAR or high resolution remote sensing images. However, the task of designing an optimal ANN for a particular problem is still challenging. For instance, if an ANN has no or too few hidden nodes it might not be able to distinguish complex patterns. On the other hand, an ANN with too many nodes or layers might be affected by noise in the data, which leads to poor generalization or training in the end. The optimal overall architecture might depend on input/output vector sizes, training and test data sizes, and the characteristics of the problem. In those works with a single (fixed) classifier, the overall performance directly depends on the choice of the classifier and its parameters. Moreover, the feature set and the number of classes are usually kept as limited as possible to avoid the related increased training complexity and the well-known "curse of dimensionality" phenomenon. Feature selection or feature dimension reduction techniques such as principal component analysis (PCA) are, therefore, commonly applied in this context. Feature and class scalabilities are also major challenges since those systems with a single, fixed classifier cannot be used whenever a new feature or class is introduced.

To address these problems and hence to maximize the classification accuracy, in this paper we propose to use a novel collection of a network of binary classifier (CNBC) framework [6], which is designed to seek an optimal classifier architecture for each distinct SAR image class type and feature set whilst utilizing a large set of major features within. Specifically in this approach, the following objectives are targeted:

I. Evolutionary Search: seeking for the optimum network architecture among a collection of configurations (the so-called Architecture Space, AS).

II. Evolutionary Update in the AS: keeping only "the best" individual configuration in the AS among indefinite number of evolution runs.

III. Feature Scalability: support for varying number of features. Any feature can be dynamically integrated without requiring starting from the beginning.

IV. Class Scalability: support for varying number of classes.

V. High efficiency for the evolution (or training) process: using as compact and simple classifiers as possible in the AS.

VI. Parallel processing: classifiers can be evolved using several processors working in parallel.

In order to achieve all these objectives, CNBC is designed to adopt a "Divide and Conquer" type of approach. Each individual NBC in the CNBC body is devoted to a unique SAR terrain class and further encapsulates a set of evolutionary binary classifiers (BCs) discriminating the class of the NBC with a unique feature set (or sub-feature). The optimality *therein* can be set with a user-defined criterion. Once the evolution process is completed for all individual BCs in all NBCs, CNBC can then be used to classify an entire SAR image into predefined terrain classes. Furthermore, such a collective network structure allows us to dynamically adapt when new classes are introduced to the current or another SAR image (e.g. finer differentiation of urban areas for particular applications) while performing only *incremental* evolutionary updates over some NBCs, if needed. This can in turn be a significant advantage when the current CNBC is used to classify other SAR images with similar classes since no or only minimal (*incremental*) evolutions are thus needed.

The rest of the paper is organized as follows. Section II presents the CNBC framework along with its incremental evolutionary update mechanism. Section III makes a brief introduction to major polarimetric SAR features used. Section IV provides classification results and comparative evaluations over the AIRSAR image of San Francisco Bay. Finally, Section V concludes the paper and discusses topics for future work.

II. SAR IMAGE CLASSIFICATION

As shown in Figure 1, the main idea in this approach is to use as large number of classifiers as necessary, so as to divide a massive learning problem into many NBC units along with the BCs within, and thus prevent the need of using complex classifiers as the performance of both training and evolution processes degrades as complexity rises. Each NBC corresponds to a unique SAR image

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class and encapsulates certain number of BCs in the input layer where each BC performs classification using a single feature vector (FV), the dimension of which determines the input layer size. Therefore, whenever a new feature is extracted, its corresponding BC will be created and inserted into each NBC, keeping the other BCs unchanged. On the other hand, removing an existing feature corresponds to simply remove the BC from each NBC in the system.

Each NBC has a "fuser" BC in the output layer, which collects and fuses the binary outputs of all BCs in the input layer and generates a single binary output, representing the relevancy of each FV to the NBC's corresponding SAR image class. Furthermore, CNBC is also scalable to any number of classes since whenever a new class is defined by the user, a new NBC can simply be created (and evolved) for this class without or minimal change to the other NBCs. Changes might be reflected in evolving the other NBCs with the newly available training data of the new class(es). This way the overall system is able to dynamically adapt to user demands for varying number of SAR image classes.

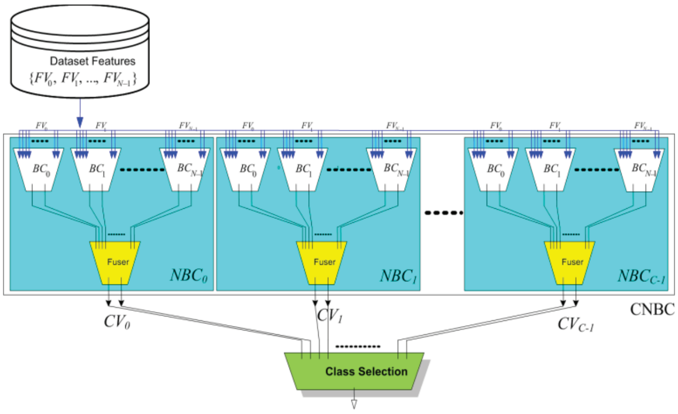

Figure 1 - Topology of the proposed CNBC with C classes and N FVs.

As shown in Figure 2, the evolution session of a subset of NBCs or the entire CNBC is performed for each NBC individually with a two-phase operation. Using the feature vectors (FVs) and the target class vectors (CVs) of the training dataset, the evolution process of each BC in a NBC is performed within a defined architecture space (AS, see [4] for details) in order to find the best BC configuration with respect to a given criterion (e.g. training MSE or classification error) using e.g. MD PSO [5] or exhaustive Back Propagation. Each evolution process may contain several runs and the best configuration achieved will be used as the final BC classifier. Note that NBCs associated with those classes in the training dataset are only involved into the evolution process whereas the others can be kept "as is".

During Phase 1 (see top of Figure 2), the BCs of each NBC are first evolved given an input set of FVs and a target CV. Recall that each CV is associated with a unique NBC and the fuser BCs are not involved in this phase. Once the evolution process is completed for all BCs in the input layer (Phase 1), the best BC configurations are used to forward propagate the FVs of the training dataset to compose the FVs of the fuser BC from their output CVs, so as to evolve the fuser BC in the second phase (see the bottom of Figure 2). In this phase, the fuser BC learns the significance of each individual BC (and its feature) for the discrimination of that particular class. Similarly, each BC in the first layer shall in time learn the significance of individual feature components of the corresponding FV for the discrimination of its class. In short the CNBC, if properly evolved, shall learn the significance (discrimination power) of each FV and its individual components.

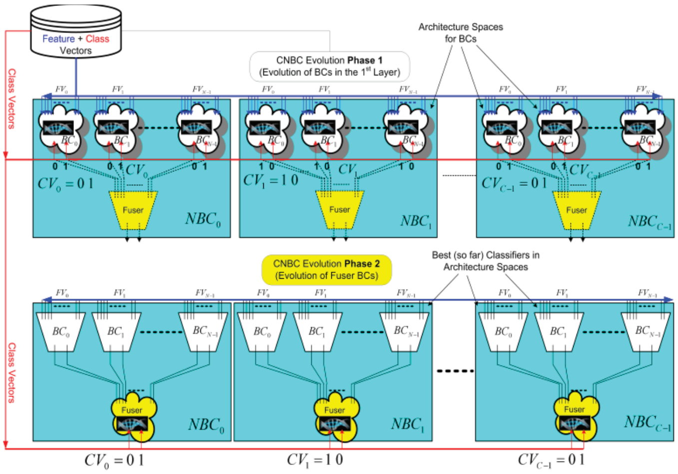

Figure 2 - Illustration of the two-phase evolution session over BCs' architecture spaces in each NBC

The evolution process of an existing CNBC is two-fold and can be performed either by incremental evolution sessions on top of the existing NBCs when the new training data is available for them or by an initial evolution when a new class is introduced. The latter might further require incremental evolutions over some of the existing NBCs if this new data cannot be classified correctly by those corresponding NBCs. In an incremental evolution, all configurations in the AS of a BC will be trained with the new training data and as a result of this, for any BC in the NBC, in this paper a new ANN, which surpasses the previous best configuration, may emerge and thus be used afterwards.

III. POLARIMETRIC SAR FEATURES

Polarimetric SAR (PolSAR) features can generally be divided into two categories: the first group belongs to the features extracted directly from the polarimetric SAR data and its different transforms such as the scattering matrix, from which the Stokes matrix, the covariance matrix, and the coherency matrix can be derived whereas the second group is based on the polarimetric target decomposition theorems, which are used for information extraction in PolSAR. Each feature has its own strength and weaknesses for discriminating different SAR class types and this fact has been approved by several recent works such as [8] and [9], which concluded that employing multiple features and different combinations can significantly improve SAR image classification. Hence, we shall also use a large set of features from both groups.

PolSAR systems often measure the complex scattering matrix, S, produced by a target under study with the objective to infer its physical properties. Assuming linear horizontal and vertical polarizations for transmitting and receiving, S is expressed as

$$\boldsymbol{S} = \begin{bmatrix} \boldsymbol{S}_{hh} & \boldsymbol{S}_{hv} \\ \boldsymbol{S}_{vh} & \boldsymbol{S}_{vv} \end{bmatrix}. \tag{1}$$

There are several coherent target decomposition theorems [2], such as the Krogager decomposition, the Cameron decomposition, and SDH (Sphere, Diplane, Helix) decomposition, all of which aim to express the measured *S* as the combination of scattering responses of coherent scatterers. Alternatively, the second order polarimetric descriptors of the 3x3 average polarimetric covariance C and coherency T matrices can be derived from S.

Incoherent target decomposition theorems [2] such as the Freeman decomposition, the Huynen decomposition, and the Cloude-Pottier decomposition employ the covariance matrix or coherency matrix of PolSAR data to characterize distributed scatterers. Cloude and Pottier [2] have developed the H/A/α decomposition which is based on eigenanalysis of the polarimetric coherency matrix. C is expressed as a sum of three real eigenvalues $\lambda_1 > \lambda_2 > \lambda_3 \geq 0$ and the corresponding eigenvectors e_i. They also defined entropy H, anisotropy A, and a set of four average angles $\bar{\alpha}$, $\bar{\beta}$, $\bar{\delta}$, and $\bar{\gamma}$ for analysis of the physical information related to the medium scattering characteristics. Additionally, information about the target's total backscattered power can be determined by the *Span* defined as the sum over λ_i. Moreover, there are other measures derived from PolSAR data such as three complex correlation coefficients (ρ_{12}, ρ_{13}, ρ_{23}) between scattering matrix terms.

As a result, the following three sets of feature vectors FV_n, are formed as input (sub-) features for the used CNBC. Each FV has the following components selected from the aforementioned features:

$$FV_1 = [T_{11}, T_{22}, T_{33}, C_{11}, |C_{12}|, \angle C_{12}, |C_{13}|, \angle C_{13}, C_{22}, |C_{23}|, \angle C_{23}, C_{33}] \quad (2)$$

$$FV_2 = [Span, H, A, \bar{\alpha}, \bar{\beta}, \bar{\delta}, \bar{\gamma}, \lambda_1, \lambda_2, \lambda_3] \quad (3)$$

$$FV_3 = [|\rho_{12}|, \angle\rho_{12}, |\rho_{13}|, \angle\rho_{13}, |\rho_{23}|, \angle\rho_{23}] \quad (4)$$

For the purpose of normalizing and scaling each feature vector, first the logarithm of magnitude features in FV_1, *Span* and the three eigenvalues in FV_2 are taken before all features are linearly scaled into [-1, 1]. Finally, the feature vectors are histogram equalized which was found to be more effective for visualization and training.

IV. EXPERIMENTAL RESULTS

The benchmark dataset used for visual evaluation is the NASA/Jet Propulsion Laboratory Airborne SAR (AIRSAR) L-band data of the San Francisco Bay (SFBay). The original four-look fully polarimetric SAR data, having a dimension of 900x1024 pixels, provides good coverage of natural (sea, mountains, forests) and man-made targets (buildings, streets, parks, roads). We defined 5 distinct classes for natural area (such as *water - sea, mountain – cliffs – rocks, forest - trees, flat zones* such as beach, grass) and *urban* area (buildings, streets, roads) targets with a more complex inner structure. Data was preprocessed using speckle filtering as recommended by Lee et al. [7] over a 5x5 window.

The CNBC created for the SFBay dataset contains the same number of NBCs as the number of pre-defined classes (in this case 5). Recall that each NBC within the CNBC contains the number of BCs identical to the number of FV sets with the addition of the fuser BC. Therefore, in our case each NBC has 4 BCs (3 BCs in the input layer + fuser BC) and thus a total of 5x4=20 Multi-Layer Perceptron (MLP) classifiers are individually evolved using exhaustive Back Propagation (BP). Furthermore, note the input layer size of each BC is determined by the size of its FV_n, i.e. 12, 10 and 6, respectively, for the input layer BCs of all NBCs, and naturally, 3x2 = 6 for all fuser BCs.

The evolution (and training) parameters and internal settings of the MLPs are as follows: the learning parameter for BP is $\eta = 0.002$, the iteration number is 1000, and the activation function is the hyperbolic tangent. For the MLP AS, we used the simplest configurations within the following range arrays: $R_{min} = \{N_i, 8, 2\}$ and $R_{max} = \{N_i, 16, 2\}$, which indicate that besides the single layer perceptron, all MLPs have only one hidden layer with 8 to 16 hidden neurons. Note that the input N_i depends on the size of FV_n. Finally, for the evolution method which seeks for the optimal configuration, 10 independent BP runs are performed for each configuration in the AS and the best one is selected.

Our 3-step experimental setup is as follows. We first create and evolve a CNBC for 3 classes (*water*, *urban*, *forest*) using the training dataset of SFBay. Then, in step 2, we add the *flat zone* class and finally insert the *mountain* class in step 3. After each step the CNBC is incrementally evolved with the new training data available for the new class, which is also verified over the existing NBCs, i.e. whether or not the new data yields a classification error exceeding 5%. If this is the case for a particular NBC then it will be subject to an incremental evolution; otherwise, it will be kept as is. Table 1 summarizes the classes used in each step with their number of class training samples and the classification error obtained *before* the upcoming incremental evolution process.

Table 1 - Incremental evolutions with the addition of new classes.

Step	Class	No. of class training samples	Classification Error
1	*water* *urban* *forest*	171 195 180	-
2	*+flat zone*	221	*water*: 151 (68%) *urban:* 46 (21%) *forest*: 24 (11%)
3	*+mountain*	188	*water*: 9 (4.8%) *urban*: 0 (0%) *forest:* 95 (50.5%) *flat zone*: 84 (44.7%)
		955	

It can be seen that adding the *flat zone* class in step 2 required an incremental evolution for all NBCs (classes) whereas for the *mountain* class addition in step 3 NBCs for the *water* and *urban* class were kept "as is". Classification results of the proposed CNBC over the SFBay image are shown in Figure 3 B, C and D for three, four and five classes, respectively.

For comparative evaluations, classification results from two recently published supervised techniques (a 3-layer ANN [11] and Optimization of Polarimetric Contrast Enhancement (OPCE) [10]) are shown in Figure 4 A and B. The 3-layer ANN is applied only over a sub-area (600x600 pixels) of the SAR image with 3 classes, *water*, *urban* and *forest,* see Figure 4A. They used more than 26000 pixels for training with a 19-D feature vector which has been reduced to 10-D by PCA. Although with minimal number of classes used and a massive size of training samples, it is evident that this method has large misclassified sections, particularly in the *water* and *mountain* (or *forest*) terrains. OPCE is also applied over a sub-area of 700x900 pixels (Figure 4B) with 4 classes, *water*, *urban*, *forest* (or woods) and quasi-natural (equivalent of *flat zone* class in the current work), and still suffered from excessive noise and misclassified sections in the *sea* and *mountain* (or *forest*) terrains.

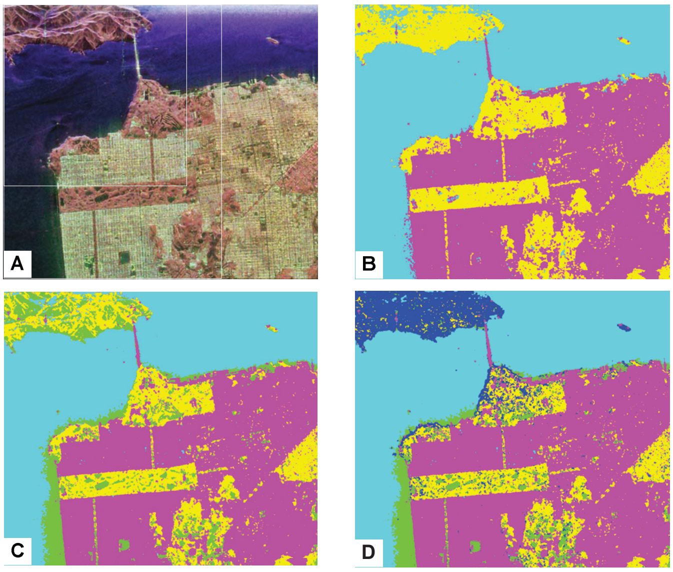

Figure 3 - A) original SFBay data {lines mark sub-sections of Figure 4 A and B} and its classification results of B) CNBC 3 classes, C) CNBC 4 classes, D) CNBC 5 classes - {*water*:cyan, *urban*:pink, *forest*:yellow, *flat zone*:green, *mountain*:blue}.

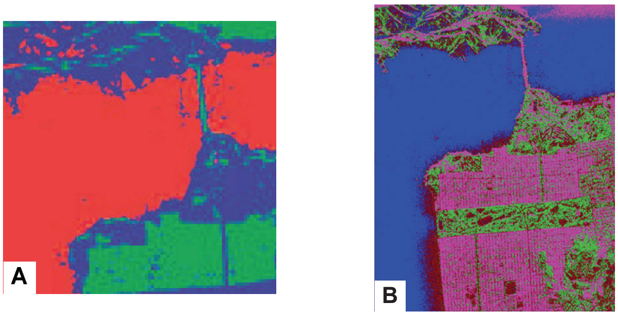

Figure 4 – Classification results for SFBay of A) ANN-based [11] 3 classes { *water*:red, *urban*:green, *forest*:blue}, B) OPCE [10] 4 classes { *water*:blue, *urban*:pink, *forest*:green, *flat zone*:brown}.

V. CONCLUSIONS

In this paper, a dedicated application of the recent CNBC framework is introduced to achieve high accuracy and efficiency for the full polarimetric SAR image classification problem. The CNBC mainly adopts a “Divide and Conquer” approach, so as to handle large number of SAR features and classes in an effective way. In the proposed approach, the optimum classifier configuration for the classification problem in hand can be sought within in the architecture space, which encapsulates a family of compact binary classifiers (BCs). This allows creating a dedicated BC to discriminate a certain class type among others with the use of a single (sub-) feature. Evolution process in an existing CNBC related to a new SAR classification task is achieved *incrementally* by using new training data.

Experiments over the AIRSAR San Francisco data set show promising results compared to the recent (static) classification methods. Although the results indicate that all the aforementioned objectives have been fulfilled, even higher accuracy levels can still be expected with the addition of new powerful SAR features as well as image processing features extracted from the color, texture, and edge information. With such high accuracy levels, we can further foretell that a CNBC evolved for one SAR image can then be used “as is” or perhaps with (minimal) incremental evolutions, to classify related SAR images with similar terrain classes. This may even be further extended into a retrieval framework for SAR image databases where SAR image(s) with certain class type(s) can be queried and retrieved. These are all subjects of future work.

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