SAR IMAGERY CLASSIFICATION IN EXTENDED FEATURE SPACE BY COLLECTIVE NETWORK OF BINARY CLASSIFIERS

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ABSTRACT

Polarimetric SAR image classification has been an active research field where several features and classifiers have been proposed in the past. Using numerous features can be a desirable option so as to achieve a better discrimination over certain classes, yet key questions such as how to avoid "Curse of Dimensionality" and how to combine them in the most effective way still remains unanswered. In this paper, we investigate SAR image classification using a large set of features, where the focus is particularly drawn on the extension of image processing features e.g. texture, edge and color. We propose a dedicated application of the Collective Network of (evolutionary) Binary Classifiers (CNBC) framework to address these problems with the aim of achieving high feature scalability. We furthermore tested several SAR and image processing feature constellations over three well-known SAR image classifiers and make comparative evaluations with CNBC. Experimental results over the full polarimetric AIRSAR San Francisco Bay and Flevoland images show that additional image processing features are able to improve SAR image classification accuracy and moreover, the CNBC proves useful and can scale well especially whenever high number of features and classes are encountered.

1. INTRODUCTION

The accurate terrain classification of polarimetric synthetic aperture radar (PolSAR) data is a major and challenging task. It has been an active research area for the last decades, where various supervised classification schemes have been proposed, i.e. ANNs [17], SVMs [18] Random Forests [20] to the recent Collective Network of Binary Classifiers [7].

Besides the application of traditional PolSAR features obtained by target decompositions, the integration of image processing features such as texture is widely used to extend the feature set within the field of SAR image classification. However, in the area of content-based image retrieval, several low-level features have been developed to characterize the color/texture/edge information of images. So far among popular edge and texture features such as Local Binary Pattern (LBP) [13], the MPEG-7 Edge Histogram Descriptor (EHD) [12], and Gabor Wavelets [11], the gray-level co-occurrence matrix (GLCM) [5] is the common texture feature used in SAR image classification [17], [18]; consequently, other image processing features such as color and edges have not yet been investigated in this area. For instance, in a recent survey article [10], covering several techniques for improving classification performance of remote sensing data, no color-based feature has been considered. For visualization purpose it is a common practice to generate pseudo-color images by mapping SAR features to each color channel. Especially several approaches have focused on better color representations of SAR images such as assigning same colors to the same scattering information [19] or investigating different scattering parameters in various color space models for visualization [16]. Even though they obviously do not provide a natural color representation, these pseudo-colors may provide useful information for terrain classification.

In order to maximize the SAR classification accuracy, in this paper, we propose a dedicated application of the Collective Network of (evolutionary) Binary Classifiers (CNBC) framework, which is designed to seek for optimal classifier architecture for each distinct terrain type and feature set whilst utilizing a large set of major features within. The CNBC further supports *varying* number of features and classes so that any feature set and SAR terrain (class) type can be dynamically integrated into the framework without requiring a full-scale set-up and re-evolution. Such dynamic feature/class scalability can be of paramount importance and can lead to an unprecedented development that has not been achieved in this field by any of the traditional classifiers mentioned earlier. Moreover, we will also examine the effects of different feature set sizes related to different training data sizes. We will conduct various experiments and make comparative evaluations of the CNBC against traditional classifiers such as Multi-Layer Perceptron, Support Vector Machines, and Random Forest. They will be tested on two widely known AIRSAR images.

The rest of the paper is organized as follows. Section 2 briefly presents the CNBC framework. Section 3 introduces the major polarimetric SAR features along with various image processing features. Section 4 provides classification results and comparative evaluations over the two AIRSAR images of San Francisco Bay and Flevoland. Finally, Section 5 concludes the paper and discusses topics for future work.

2. COLLECTIVE NETWORK OF BINARY CLASSIFIERS

The Collective Network of Binary Classifiers adopts a “Divide and Conquer” type of approach, which is based on a network of (evolutionary) binary classifiers (NBCs). Each NBC 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 with the predefined classes. Furthermore, the employed network structure allows us to simply extend the existing network when new classes are introduced into the current or another similar classification problem while performing only incremental evolutionary updates over some of the existing NBCs, if needed. This can in turn be a significant advantage when the current CNBC is used to classify SAR images with similar terrain classes since no or only minimal incremental evolution sessions are needed to adapt it to a new classification problem.

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. Each NBC corresponds to a unique SAR terrain class and encapsulates certain number of BCs in the input layer where each BC performs classification using one 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. 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 terrain class.

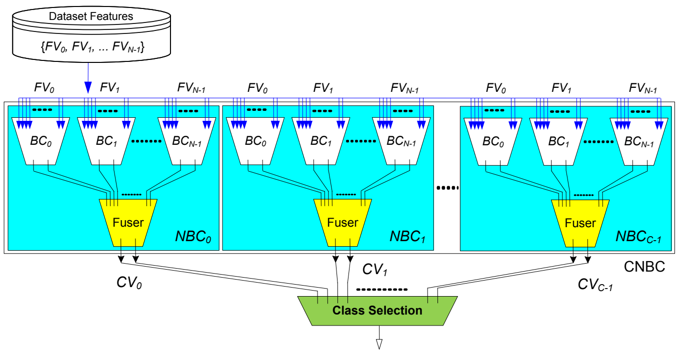

Figure 1: Topology of the proposed CNBC with C classes and N FVs.

The evolution session of the entire CNBC or a subset of NBCs 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 [6] for details) in order to find the best BC configuration with respect to a given criterion (e.g. training MSE, classification error) using e.g. MD PSO [6] or exhaustive Back Propagation for ANNs.

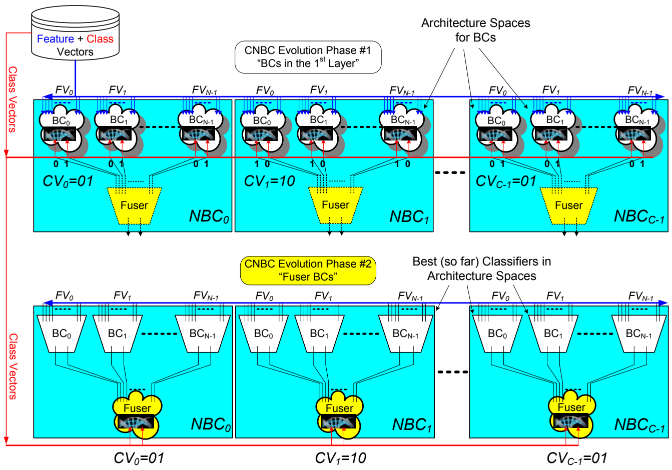

Figure 2: Illustration of the two-phase evolution session over BCs’ architecture spaces in each NBC.

During Phase 1 (top of Figure 2), the BCs of each NBC are first evolved given an input set of FVs and a target CV. Rather than fixing the configuration of the BCs, we try to find the best possible classifier from a set of configurations (i.e. in a BC, there is no training of one single configuration) for each individual feature for each particular class. Once the evolution process is completed for all BCs in the input layer (Phase 1), the best BC configurations are used in the actual classification step. The second phase (bottom of Figure 2) is needed to merge/fuse the individual BC outputs into a final NBC output (i.e. class decision). Therefore, the fuser BC is trained to learn 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. Thus, in short the CNBC, if properly evolved, shall learn the significance (discrimination power) of each FV and its individual components.

3. SAR AND IMAGE PROCESSING 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 of those features has its own strength and weaknesses for discriminating different SAR terrain class types.

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 [4], such as the *Pauli*, the *Krogager* and the *Cameron* decomposition, 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 [4] such as the *Freeman*, the *Huynen*, the *Cloude-Pottier* and *Touzi* [13] decomposition, employ the covariance or coherency matrix of PolSAR data to characterize distributed scatterers. Additionally, information about the target's total backscattered power can be determined by the *Span*. 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.

Besides extracting PolSAR features from the aforementioned target decompositions, we extract various texture features such as LBP, Gabor, and Ordinal Co-occurrence Matrix (OCM) [14] and an edge descriptor, the MPEG-7 EHD. Particularly, we focus on the utilization of several efficient color features such as Hue-Saturation-Value (HSV) color space histogram, the MPEG-7 Dominant Color Descriptor (DCD) [12], and the MPEG-7 Color Structure Descriptor (CSD) [12]. These image processing features are extracted over the pseudo-color image obtained by mapping T_{11}, T_{22}, and T_{33} from the coherency matrix T to the red, green and blue (RGB) color channels, respectively. Each individual feature is extracted for every pixel over an $(2w+1)$ by $(2w+1)$ window.

As a result, the following feature vectors, FV_N , are formed and combined into different feature sets used as input features for all classifier schemes. Each FV has the following components selected from the aforementioned PolSAR and texture/color features:

$$FV_1 = [T_{11}, T_{22}, T_{33}, C_{11}, |C_{12}|, \angle \boldsymbol{C}_{12}, |C_{13}|, \angle \boldsymbol{C}_{13}, C_{22}, |C_{23}|, \angle \boldsymbol{C}_{23}, C_{33}], \tag{2}$$

$$FV_2 = [\mathit{Span}, H, A, \bar{\alpha}, \bar{\beta}, \bar{\delta}, \bar{\gamma}, \lambda_1, \lambda_2, \lambda_3] \ (\textit{Cloude-Pottier}), \tag{3}$$

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

$$FV_4 = [|\alpha|^2, |\beta|^2, |\gamma|^2 \ (\textit{Pauli}), k_s, k_d, k_v \ (\textit{Krogager}), \alpha_s, \phi_{\alpha s}, \psi, \tau_m \ (\textit{Touzi})], \tag{5}$$

$$FV_5 = [P_s, P_d, P_v \ (\textit{Freeman}), 2\langle A_0\rangle, \langle B_0\rangle+\langle B\rangle, \langle B_0\rangle+\langle B\rangle \ (\textit{Huynen})], \tag{6}$$

FV_6 = 16 bin LBP histogram, (7)

FV_7 = 5 bin MPEG-7 EHD, (8)

FV_8 = mean and standard deviation over 3 scales and 4 orientation of Gabor wavelets, (9)

FV_9 = 3 OCM with 3 distances and 4 orientations, (10)

FV_{10} = 24 (6×2×2) bin HSV histogram, (11)

FV_{11} = the three color components and the weight of the most dominant color, (12)

FV_{12} = 32 bin CSD histogram. (13)

4. EXPERIMENTAL RESULTS

Two PolSAR images were used for numerical performance evaluations. The first one is the NASA/Jet Propulsion Laboratory Airborne SAR (AIRSAR) L-band data of the San Francisco Bay (SFBay) shown in Figure 3. The original four-look fully polarimetric SAR data of the San Francisco Bay, having a dimension of 900x1024 pixels, provides good coverage of both natural (e.g. sea, mountains, forests) and man-made terrain types (e.g. buildings, streets, parks, golf course). We defined five distinct classes for both natural (such as *water - sea, mountain - cliffs, forest - trees, flat zones* i.e. beach, grass) and *urban* area (buildings, streets, roads) with a complex inner structure. The sizes of the training and test sets are 1305 and 151441 pixels, respectively. Note that the ground truth accuracy is not 100% guaranteed for SFBay dataset. For instance, the *urban* class may also cover trees (planted alongside roads or gardens of houses), thus classification is performed by taking the majority terrain type into account. The second PolSAR image with accurate ground-truth information available (see Figure 4) is the AIRSAR L-band dataset of Flevoland, The Netherlands with a size of 1024x750 pixels and collected in mid-August 1989 during MAESTRO-1 Campaign. The Flevoland dataset is used to perform crop and land classification. There are 12 ground-truth classes in this image: *water, forest, stem beans, lucerne, roads, bare soil, grass, peas, rapeseed, beet, potatoes* and *wheat* [1]. In order to evaluate the effect of the variations in training dataset sizes, two training datasets, one with a small training sample size of 964 (called FL-1k) and the other with a larger size of 8676 (called FL-8k) pixels are used where the test dataset size is fixed to 179259 pixels. Over both images, the speckle filter suggested by Lee *et al.* [9] is employed with a 5x5 window.

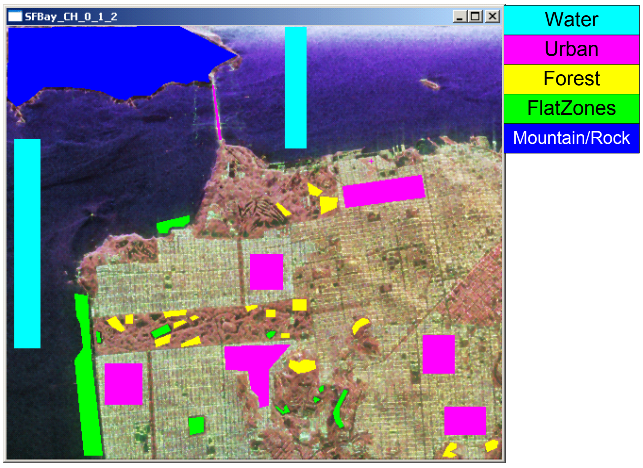

Figure 3: SFBay with its test set data (Best view in color).

In order to evaluate the performance gain/loss that can be obtained by using different set of features, as enumerated in Table 1, five different feature sets (based on the different feature vectors, FV_N , as described in Section 3) over four classification schemes are considered for the SAR classification experiments. Note, *w* is set empirically to 5 (trade-off between accuracy and visual appearance) for the local window from which the image processing features are extracted.

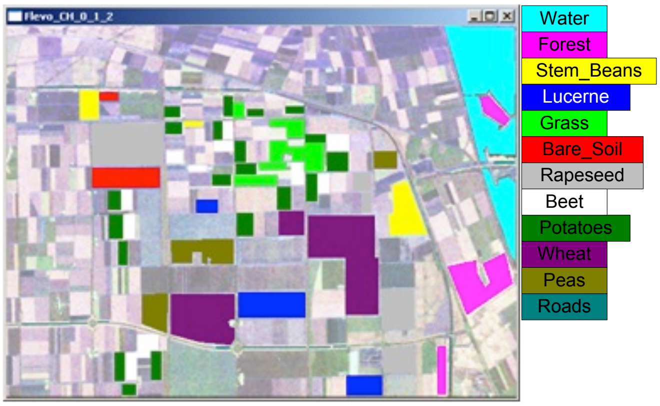

Figure 4: Flevoland and its ground truth data for 12 classes (Best view in color).

Table 1: Feature Vector Sets

Name	*FV Sets*	*Description*
SAR	$FV_1+FV_2+FV_3$	28D SAR features
SARExt	$SAR+FV_4+FV_5$	44D SAR feature extension
SARC	$SARExt+FV_{10}+FV_{11}+FV_{12}$	44D SAR + 60D color features = 104D
SART	$SARExt+FV_6+FV_7+FV_8+FV_9$	44D SAR + 81D texture features = 125D
SARTC	$SART+FV_{10}+FV_{11}+FV_{12}$	44D SAR + 81D texture + 60D color features = 185D

As for the comparing methods, we selected three commonly used classifiers namely Multi-Layer Perceptron (MLP), Support Vector Machines (SVM) and Random Forest (RF) despite the fact that none is able to provide all the capabilities CNBC does (e.g. feature and class scalability, evolutionary search and update). Since optimal BC (in this work architecture space of MLPs with a single hidden layer of 8 to 16 neurons) configurations within each NBC are searched by the underlying evolutionary search method (exhaustive Back Propagation employed with learning rate $\eta=0.002$ and 1000 epoch iterations), in order to provide a fairer comparison, the best possible classifier architectures and/or parameters are also searched for the competitors. For MLPs this means that the best possible network configuration is searched within an architecture space encapsulating several MLPs with one and two hidden layers, each of which has 8 to 16 (hidden) neurons. For SVM, we employ the libSVM library [3] using the *one-against-one* methodology [8]. To determined the best SVM parameters, a sequential search for the best kernel type among the linear (*LIN*), polynomial (*POL*), radial basis function (*RBF*) and sigmoid kernel (*SIG*) and parameters, i.e. the respectable penalty parameter, Γ (2^n; n=0,..,3) and parameter γ (2^{-n}; n=0,..,3) $\left(RBF_{\gamma}^{\Gamma}\right)$, if applicable to the kernel type (*POL*, *RBF*), is performed. Note that this is more than a simple kernel search where also the parameters are optimised. This is in favor of SVM as it is not done for either MLP case, η and epoch iterations. For the RF classifier [2], the best number of trees within the forest is also searched from 10 to 50 in steps of 10.

Table 2 and Table 3 show the classification results for FL-1k and FL-8k, respectively. For FL-1k, it is evident that larger set of features helps to improve the classification accuracy. In particular the feature sets including color features show the highest accuracy improvement, i.e. ~4-5% whereas other image processing features' contribution varies within ~0-3%. Note that both SVM and RF exhibit an inferior performance on SART compared to the one with SARExt despite the fact that the former feature set is only a subset of the latter. This is a typical case where increased feature space dimensionality degrades the overall performance. The CNBC, on the other hand, is able to improve its performance due to its "Divide and Conquer" approach where the overall classification scheme can benefit from particular classifications over individual feature sets. The FL-8k results show similar classification improvements about 2-4% for all the feature sets including color. A similar observation can also be made on the effect of increased feature dimension over the classification performance of the CNBC and the compared schemes.

Table 2: Classification results for FL-1k dataset *with best configurations*

FL-1k	***SAR***	***SARExt***	***SARC***	***SART***	***SARTC***
MLP	0.8361 *28x12x11x*	0.8526 *44x12x*	0.8748 *104x13x*	0.8530 *125x14x*	0.8813 *185x12x*
SVM	**0.8622** $\left(RBF_{0.5}^{1}\right)$	**0.8715** $\left(RBF_{0.5}^{1}\right)$	0.9093 $\left(LIN^{2}\right)$	0.8623 $\left(LIN^{8}\right)$	0.9098 $\left(LIN^{1}\right)$
RF	0.8224 *10 trees*	0.8539 *10 trees*	0.8737 *10 trees*	0.8248 *10 trees*	0.8637 *10 trees*
CNBC	0.8513	0.8643	**0.9106**	**0.8796**	**0.9103**

Table 3: Classification results for FL-8k dataset *with best configurations*

FL-8k	***SAR***	***SARExt***	***SARC***	***SART***	***SARTC***
MLP	0.8804 *28x14x*	0.8872 *44x14x*	0.9079 *104x14x*	0.8866 *125x13x*	0.9037 *185x11x*
SVM	**0.8864** $\left(RBF_{0.5}^{2}\right)$	**0.8925** $\left(RBF_{0.5}^{1}\right)$	**0.9289** $\left(RBF_{0.5}^{1}\right)$	**0.9027** $\left(RBF_{0.5}^{1}\right)$	0.9222 $\left(LIN^{2}\right)$
RF	0.8516 *10 trees*	0.8803 *10 trees*	0.9012 *10 trees*	0.8624 *10 trees*	0.8914 *10 trees*
CNBC	0.8834	0.8826	0.9138	0.8889	**0.9229**

Table 4 shows the classification results over the SFBay image. For this image it is worth mentioning that the classification results for larger feature sets are not as significant as for the Flevoland image, if any at all. This is related to the SFBay image where the five classes are already well distinguishable by the SAR features; and texture and color only have minor contributions on the classification accuracy. However, note especially that for SARC and SART feature sets only CNBC performs either equally or better compared to SAR and SARExt sets. In general, it can be seen that RF performs rather unstable which is probably due to its nature of making decisions in each tree node based on randomly drawn features. SVM and CNBC perform neck on neck especially when it comes to more challenging classification tasks with limited training data and higher number of classes as in FL-1k indicating a high level of learning and generalization ability with the least amount of data.

Table 4: Classification results for SFBay dataset *with best configurations*

SFBay	*SAR*	*SARExt*	*SARC*	*SART*	*SARTC*
MLP	0.9600 *28x8x*	0.9599 *44x8x*	0.9467 *104x*	0.9551 *125x8x*	**0.9622** *185x*
SVM	**0.9662** (LIN^4)	**0.9646** (LIN^4)	0.9571 (LIN^1)	**0.9560** (LIN^1)	0.9566 (LIN^1)
RF	0.9383 *10 trees*	0.9149 *10 trees*	0.9573 *10 trees*	0.8961 *10 trees*	0.9277 *10 trees*
CNBC	0.9512	0.9489	**0.9672**	0.9513	0.9604

5. CONCLUSIONS

In this work we focus on *using several features for SAR classification so as to achieve a better discrimination over certain classes*. A dedicated application of the CNBC framework presented mainly adopts a "Divide and Conquer" type of approach, so as to handle efficiently indefinite number of (SAR and image processing) features and (SAR terrain) classes, which otherwise may turn out to be difficult problem for a single classifier due to the well known "Curse of Dimensionality" phenomenon. We furthermore tested several SAR and image processing feature constellations over three well-known SAR image classifiers and make comparative evaluations with CNBC. Our experiments with these four different classification schemes show that especially color features, which can be easily extracted over SAR feature pseudo-color images, can significantly improve classification accuracy compared to various texture features. Experiments further indicate that CNBC is capable of improving its classification performance due to its "Divide and Conquer" approach where the overall classification scheme can benefit from particular classifications over individual feature sets. This addresses an important drawback of regular classifiers as their performance can degrade due to the well-known "Curse of Dimensionality" phenomenon. Note that classification accuracy might still be improved by extending the overall feature sets with image processing features from alternative pseudo-color images that can be created by using different SAR features; and we further plan to investigate other remote sensing data. This is subject to future work.

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REFERENCES

[1] T.L. Ainsworth, J.P. Kelly and J.-S. Lee, "Classification comparisons between dual-pol, compact polarimetric and quad-pol SAR imagery," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 64, no. 5, pp. 464-471, Sep. 2009.

[2] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5-32, 2001.

[3] C. C. Chang, C. J. Lin, LIBSVM : a library for support vector machines, 2001. (http://www.csie.ntu.edu.tw/~cjlin/libsvm).

[4] S. Cloude, E. Pottier, "A review of target decomposition theorems in radar polarimetry", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 34, no. 2, pp. 498-518, 1996.

[5] R. Haralick, K. Shanmugam, I. Dinstein, "Textural Features for Image Classification", *IEEE Transactions* on *Systems, Man and Cybernetics,* vol.3, no.6, pp.610-621, Nov. 1973.

[6] S. Kiranyaz, T. Ince, A. Yildirim, M. Gabbouj, "Evolutionary Artificial Neural Networks by Multi-Dimensional Particle Swarm Optimization", *Neural Networks*, vol. 22, pp.1448-1462, 2009.

[7] S. Kiranyaz, M. Gabbouj, J. Pulkkinen, T. Ince, K. Meissner, "Network of Evolutionary Binary Classifiers for Classification and Retrieval in Macroinvertebrate Databases", *Proc. of IEEE ICIP*, pp. 225-2260, 2010.

[8] U. Kressel, Pairwise classification and support vector machines, *Advances in Kernel Methods - Support Vector Learning,* (1999).

[9] J. S. Lee, M. R. Grunes and R. Kwok, "Classification of multi-look polarimetric SAR imagery based on complex Wishart distribution," *Internl. Journal of. Remote Sensing*, vol. 15, no. 11, pp. 2299-2311, 1994.

[10] D. Lu, Q. Weng, "A survey of image classification methods and techniques for improving classification performance", *Internl. Journal of Remote Sensing*, vol. 28, no. 5, pp. 823-870, Jan. 2007.

[11] B. Manjunath, P. Wu, S. Newsam, H. Shin, "A texture descriptor for browsing and similarity retrieval", *Journal of Signal Processing: Image Communication*, vol. 16, pp. 33-43, Sep. 2000.

[12] B. S. Manjunath, J. R. Ohm, V. V. Vasudevan, and A. Yamada, "Color and Texture Descriptors", *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 11, pp. 703-715, Jun. 2001.

[13] M. Pietikäinen, T. Ojala, "Rotation-invariant texture classification using feature distributions", *Pattern Recognition*, vol. 33, pp. 43-52, 2000.

[14] M. Partio, B. Cramariuc, M. Gabbouj, "An Ordinal Co-occurrence Matrix Framework for Texture Retrieval," *EURASIP Journal on Image and Video Processing*, vol. 2007, Article ID 17358, 15 pages, 2007.

[15] R. Touzi, "Target scattering decomposition of one-look and multi-look SAR data using a new coherent scattering model: the TSVM", *IEEE Geoscience and Remote Sensing Symposium*, pp. 2491- 2494, Sep. 2004.

[16] P. Wang, W. Hong, F. Cao, "Investigation of the scattering intensity parameters and the hue-saturation based color space models used in the Cloude-Pottier decomposition method" *IET Internl. Radar Conference,* pp.1-4, Apr. 2009.

[17] D. Zhang, L. N. Wu, G. Wei, "A new classifier for polarimetric SAR images", *Progress In Electromagnetics Research 94*, pp.83-104, 2009.

[18] L. Zhang, B. Zou, J. Zhang, Y. Zhang, "Classification of Polarimetric SAR Image Based on Support Vector Machine Using Multiple-Component Scattering Model and Texture Features" *EURASIP Journal on Advances in Signal Processing*, vol. 2010, Article ID 960831, 9 pages, 2010.

[19] X. Zhou; C. Zhang, "A perceptive uniform pseudo-color coding method of SAR images", *Internl. Conference on Radar*, pp.1-4, Oct. 2006.

[20] T. Zou, W. Yang, D. Dai, H. Sun, "Polarimetric SAR Image Classification Using Multifeatures Combination and Extremely Randomized Clustering Forests", *EURASIP Journal on Advances in Signal Processing*, vol. 2010, Article ID 465612, 9 pages, 2010.