Polarimetric SAR Image Classification by Using Artificial Neural Network

V Turkar
Center of Studies in Resource Engineering
IIT Bombay, Powai, Mumbai-400 076, India
9920038965
varshaturkar@iitb.ac.in

ABSTRACT
The classification of various land cover features using fully polarimetric Synthetic Aperture Radar (SAR) data sets is an important application of radar remote sensing. The data acquired is over various parts of India are SIR-C L- and C-band data over Kolkata city and its surroundings. The field work was carried out in April 2009. Similarly, PALSAR quad pol data over several areas is acquired. The proposed classifier is based on the artificial neural network which is developed in Matlab and it makes use of backscattering values. It is a supervised classification technique which is applied on the ALOS PALASR and SIR-C data. The classification accuracy after applying different speckle filters is compared with the classification accuracy obtained without applying filter. It is also compared with minimum distance and maximum likelihood techniques.

Categories and Subject Descriptors
I.4.7 Image Processing and Computer vision

General Terms
Experimentation

Keywords
Radar polarimetry, synthetic aperture radar, speckle, neural network, classification.

1. INTRODUCTION
Classification of polarimetric SAR images has become a very important topic after the availability of Polarimetric SAR images through ENVISAT ASAR, ALOS PALSAR SIR-C and Radarsat-2. Classification is the task of assigning a set of given data elements to a given set of labels or classes such that the cost of assigning the data element to a class is minimum. Radar polarimetry is a technique for classification of land use features. Several investigations have reported the use of polarimetric data to map earth terrain types and land covers ([1], [2], [3], [4], [5]). The two main techniques for image classification are supervised and unsupervised classification techniques. An unsupervised classification technique, classifies the image automatically by finding the clusters based on certain criterion. On the other hand in supervised classification technique the location and the identity of some cover type, for example urban, forest, and water are known before.

The data is collected by a field work, maps, and personal experience. The analyst tries to locate these areas on the remotely sensed data. These areas are known as "training sites". An analyst can guide a classifier with the help of these training sites to learn the relationship between the data and the classes. This manual technique of selecting training sets could be difficult when ground truth is not available.
In this paper a new technique is proposed using ANN. It is a supervised classification technique which makes use of the backscattering values of the PolSAR data. The proposed method is developed in MATLAB.

2. BACKSCATTERING
The scattering properties of radar can be measured by polarimetric radar which can be used to improve the classification accuracy. The target is illuminated by a radar system with an incident wave and the wave is scattered in all direction by the target. Some of the part of the scattered wave which is directed back towards the receiving antenna is recorded by the radar system. The received energy is called backscatter. There are three types of backscattering: single bounce, double bounce and volume scattering. Backscatter mechanisms include direct backscatter from branches (single bounce/volume scattering), backscatter from trunks (single bounce), scattering from branch-ground interaction, man made objects (double bounce), scattering from trunk-ground interaction (double bounce), and direct backscatter from the ground (surface scattering). In case of dual polarized radars all four channels are not received so entire scattering properties of the target can not be obtained. For classification of SAR images, backscattering values $\boldsymbol{\sigma}^0$ and their distribution for various features are very important. The study of backscattering values for various land covers for different sensors will help in improving the classification accuracy. The $\boldsymbol{\sigma}^0$ values for different land features for different sensors are observed. These backscattering values can be used as signatures in supervised classification techniques. Special software is developed for converting complex digital numbers (DN) into backscattering coefficient ($\boldsymbol{\sigma}^0$) for all sensor systems.

3. CLASSIFICATION USING ANN
Supervised classification methods for the polarimetric SAR data can be divided into statistical and neural network approaches. Neural network techniques (Hara, 1994; Chen *et al,* 1996)[6][7] have also been applied using the complete polarimetric information as input, and iterative training was normally necessary; Chen *et al.*(Chen *et al,* 1996)[7] applied a dynamic learning neural network and fuzzy neural network to classify multifrequency POLSAR. Ito *et al.* (1998) [8] have proposed a classification method using a

competitive neural network trained by only two Learning Vector Quantization (LVQ) algorithms. A method which selects a suitable feature vector using the JM distance is proposed. In addition, they introduce a pseudo-relative phase between polarimetries in order to obtain higher classification accuracy. Hellmann (1999) [9] has proposed a classification based on H-alpha decomposition theorem extended by the use of the first eigen value of the coherency matrix. Fuzzy logic as well as ANN strategies is used to improve the classification accuracy. Lorenzo Bruzzone (2004) [10] integrates an advanced pattern recognition methodology (based on machine learning techniques) with an accurate feature extraction phase (bases on the SAR signal physics analysis) for better classification accuracy. To classify a pattern, certain attribute values from that pattern are input into the directed graph at the corresponding source nodes. There is one sink node for each class. The output value that is generated indicates the probability that the corresponding input pattern belongs to that class. The pattern will then be assigned to the class with the highest probability of membership. The learning process modifies the labeling of the arcs to better classify patterns. After the classification is done for the training set the results are compared with the actual classification and the accuracy is computed. Learning process continues with different weights and with all the training data or until the classification accuracy is adequate.

Steps followed in NN classifier:

1. Determine the number of output nodes as well as what attributes should be used as input.
2. The number of hidden layers (between the input and output nodes) also must be decided.
3. Determine weights and activation functions to be used for the graph.
4. For each pattern in the training set, propagate it through the network and evaluate the output predication to the actual result. If the predication is accurate then adjust weights to ensure that this predication has a higher output weight the next time. If the predication is not correct then adjust the weights to provide a lower output value for this class.
5. Steps are repeated till all the patterns are classified to the appropriate classes.

4. SUPERVISED LEARNING

The NN starting state is modified based on feedback of its performance with the data in the training set. This type of learning is referred to as *supervised* because it is known in advance what the desired output should be. Supervised learning in an NN is the process of adjusting the arc weights based on its performance with a vector or pattern or input from the training set. The classes of the training data is known a priori and thus can be used to fine tune the network for better accuracy. Thus the training set can be used as a "teacher" during the training process. The output from the network is compared to this known desired behavior.

One major problem with supervised learning is that error may not continually reduce. It is expected that each iteration in the learning process reduces the error so that it is ultimately below an acceptable level. This is not always the case. This is may be due to the error calculation technique or to the approach used for modifying the weights. NN do not guarantee convergence or optimality. The supervised algorithm must be able to calculate the error and must have some technique to adjust the weights. The error is the difference between the desired result and actual result. The mean squared error (MSE) is computed for all the nodes in the network. The entire training set is considered while computing MSE. Then the weights are adjusted according to the error to get better accuracy.

5. PROPOSED METHOD

The algorithm is developed in MATLAB R2009. It uses a back propagation algorithm.

Preprocessing:

1. For ALOS PALSAR or SIR-C quad polarization data the following files are created by using the software which is specially designed by CSRE, IIT Bombay which converts the values in decibels. The software creates a (backscattering) db file for each band.
   - Alos_HH_db
   - Alos_HV_db
   - Alos_VV_db
2. The files are combined to get a three band image (for ex. alos_hh_hv_vv_db).

Creating training sites:

1. The ROI (region of interest) are taken from the alos_hh_hv_vv_db image for different land cover types like water, forest, marshy land, urban land using ENVI.
2. The ROI's are converted into the ASCII values and then to .csv (comma separated by values) files.

Creating test sites:

1. The test sites are created same as training sites.
2. The precaution is taken while taking the ROI's. The ROI should be geographically at different location than the training sites.
3. The subset of the training data can be used as a testing data.

Algorithm for classification using ANN:

The code builds a classifier that can identify the land cover from the backscattering values which are in db. There are three values each for HH HV and VV band. The problem on hand is to identify the land cover given the observed values for each of these three bands. The three band values will act as inputs to a neural network and the land cover type of the image will be target. Given an input, which constitutes the three observed values, the neural network is expected to identify if the land cover is forest or river. This is achieved by presenting previously recorded inputs to a neural network and then tuning it to produce the desired target outputs. This process is called neural network training.

The steps in the algorithm are:

[1] Preparing the data
Data for classification problems can very often have textual or non-numeric information. In our case, classes are non-numeric (Forest/River/Water). Neural networks however cannot be trained with non-numeric data. Hence there is a need to translate the textual data into a numeric form. There are several ways to translate textual or symbolic data into numeric data. Some of the common symbol translation techniques used is unary encoding, binary encoding and

numbering classes. So unary encoding is used in this code to perform symbol translation. The first three columns of data gives HH, HV and VV values in db the forth column gives the class. The four classes for ex. Forest, Marshy, Urban and Water can be represented as [1 0 0 0], [0 1 0 0], [0 0 1 0] and [0 0 0 1] respectively.

[2] Preprocess the data into a form that can be used with a neural network. The neural network object in the Matlab toolbox expects the samples along columns and its features along rows. Our dataset has its samples along rows and its features along columns. Hence the matrices have to be transposed.

[3] Building the neural network classifier
The next step is to create a neural network (feed forward back propagation network) that will learn to identify the classes. Since the neural network starts with random initial weights, the results will differ slightly every time it is run. The random seed or twister is set to avoid this randomness.

[4] A 1-hidden layer feed forward network is created with 16 neurons in the hidden layer.

[5] Now the network is ready to be trained. The samples are automatically divided into training, validation and test sets. The training set is used to teach the network. Training continues as long as the network continues improving on the validation set. The test set provides a completely independent measure of network accuracy.

[6] Testing the classifier.
The trained neural network can now be tested with the testing samples. This will give us a sense of how well the network will do when applied to data from the real world. If require the testing can be done with a separate testing set which is created while creating training set.

[7] Computation of classification accuracy using confusion matrix.
The network response can now be compared against the desired target response to build the classification matrix which will provide a comprehensive picture of a classifiers performance.

6. DATA ACQUIRED

SIR-C L- and C-band data over Kolkata city and its surroundings were freely available online. The data was in MLC (multi-look complex) format with 4.8 multilook factors with pixel size of 12.5 meters. The data is acquired in October 1994 in quad polarizations mode. Similarly, ALOS PALSAR data over Bishnupur, Bankura district, West Bengal is acquired in April 2007, March 2007 and March 2009 in quad polarizations mode. The field work is carried out in April 2009. The ALOS PALSAR DUAL POL data over Mumbai region is acquired in June 16, 2007

7. RESULTS

The ALOS PALSAR Mumbai Dual polarization data is processed using neural classifier. The results are compared with minimum distance and maximum likelihood classifier and ENVI neural network classifier. The classes follow nearly Gaussian distribution. Confusion matrix for proposed neural network classifier is given in table no. 1. Here we have taken the testing sites which are geographically at different location than the training sites. From the confusion matrix classification accuracy is computed. It is clearly seen that the neural network classifier gives best classification accuracy. After applying the Lee speckle filter before classification; the accuracy is further improved. The proposed NN classifier gives the maximum classification accuracy than the minimum distance and maximum likelihood classifiers. When the data is processed by ENVI neural classifier it is found that the classification accuracy is around 45% which is much less than the proposed neural network classifier.

Table.1. Confusion Matrix for Mumbai ALOS PALSAR Dual Pol Data Processed by NN Classifier.

Total testing samples: 5734

Ref / Classified	Water	Marshy	Urban	Forest	User's Accuracy
Water	2328	46	0	0	98.06%
Marshy	19	978	10	65	91.23%
Urban	0	11	892	493	63.89%
Forest	0	408	123	361	40.47%
Producer's Accuracy	99.19%	67.77%	87.02%	39.28%	

(a) Without Filter (Percentage Correct classification : 79.508197%)

Ref / Classified	Water	Marshy	Urban	Forest	User's Accuracy
Water	2347	0	0	0	100%
Marshy	0	1084	0	131	89.22%
Urban	0	0	980	3	99.69%
Forest	0	359	45	785	66.02%
Producer's Accuracy	100%	75.12%	95.61%	85.42%	

(b) With Filter (Percentage Correct classification : 90.617370%)

Figure 1 shows ALOS PALSAR Dual polarized image before classification. A subset of this image is processed by the proposed method and the result is shown in figure 2. Similarly different data sets from ALOS PALSAR and SIR-C are processed. The result for SIR-C L-band Kolkata area is shown in the figure 3.

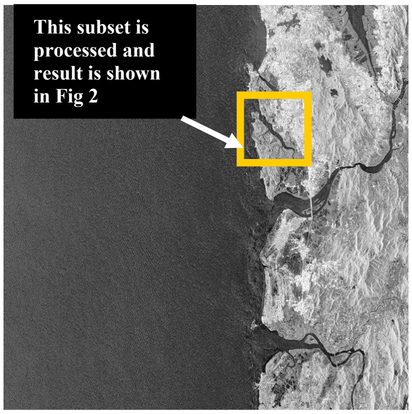
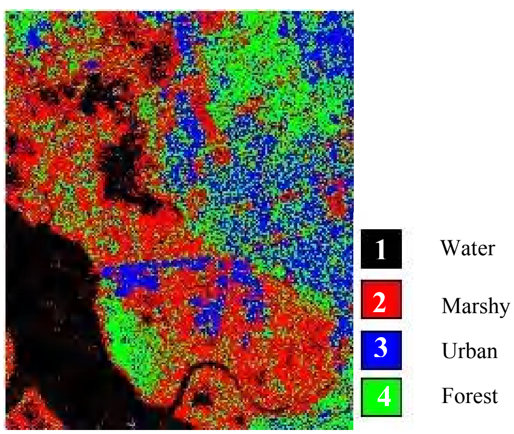


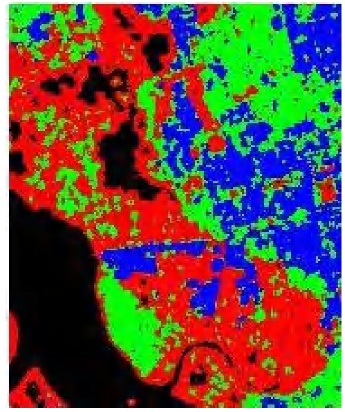
Figure 1: Alos_hh_hv_db before Classification without Applying Filter. (Mumbai region: Dual Pol Data)

(a) Before Classification



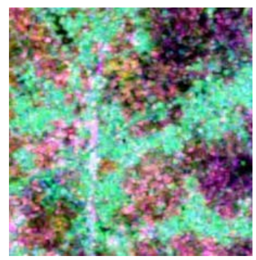
(b) Neural Classifier without filter

The proposed ANN classifier gives best results as compared to the existing classifiers. The limitation of the proposed

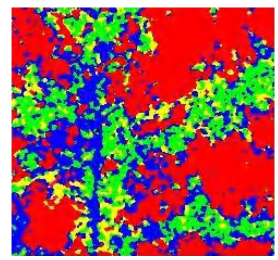


(c) Neural Classifier with filter

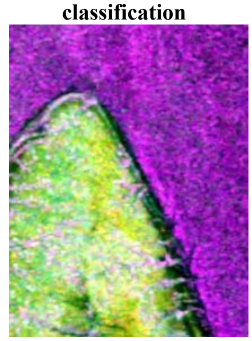
Figure 2: Subset of Mumbai ALOS PALSAR Dual Pol Data after classification.



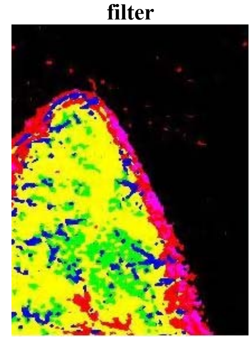
(a) Fields and Vegetation before classification



(b) Fields and Vegetation after classification with Lee filter



(d) Marshy and Sea area before classification



(e) Marshy and Sea area after classification with Lee filter

1: Vegetation, 2: Urban, 3: Fields, 4: Marshy, 5: Water, 6: Sea

Figure 3: The Images Processed by Neural Network Classifier with or without Applying the Speckle Filter

8. CONCLUSION

The backscattering value is an important parameter which can be used to classify the POLSAR data. The IDAN and LEE are the best speckle filters which improves the classification accuracy significantly.

ANN classifier is it will classify the targets properly only if they have different scattering properties. For targets having similar or little different scattering properties this classifier may not work properly. In this situation we have to consider some more parameters like texture with backscattering properties.

9. ACKNOWLEDGMENTS

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