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TEXTURE BASED LAND COVER CLASSIFICATION ALGORITHM USING GABOR WAVELET AND ANFIS CLASSIFIER

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Abstract
Texture features play a predominant role in land cover classification of remotely sensed images. In this study, for extracting texture features from data intensive remotely sensed image, Gabor wavelet has been used. Gabor wavelet transform filters frequency components of an image through decomposition and produces useful features. For classification of fuzzy land cover patterns in the remotely sensed image, Adaptive Neuro Fuzzy Inference System (ANFIS) has been used. The strength of ANFIS classifier is that it combines the merits of fuzzy logic and neural network. Hence in this article, land cover classification of remotely sensed image has been performed using Gabor wavelet and ANFIS classifier. The classification accuracy of the classified image obtained is found to be 92.8%.

Keywords:
ANFIS, Gabor Filters, Texture Analysis, Land Cover Classification, Big Data

1. INTRODUCTION

Land cover refers to the biophysical characteristics of the surface of the earth. Texture is a surface property of land covers defined by tone and structure where tone refers to pixel intensities and structure refers to relationship between pixel intensities in a local region. Land cover classification implies classifying the multispectral remotely sensed image into various land covers such as land, vegetation, water, etc. The choice of feature extracted and classifier employed determines the classification accuracy obtained in classification.

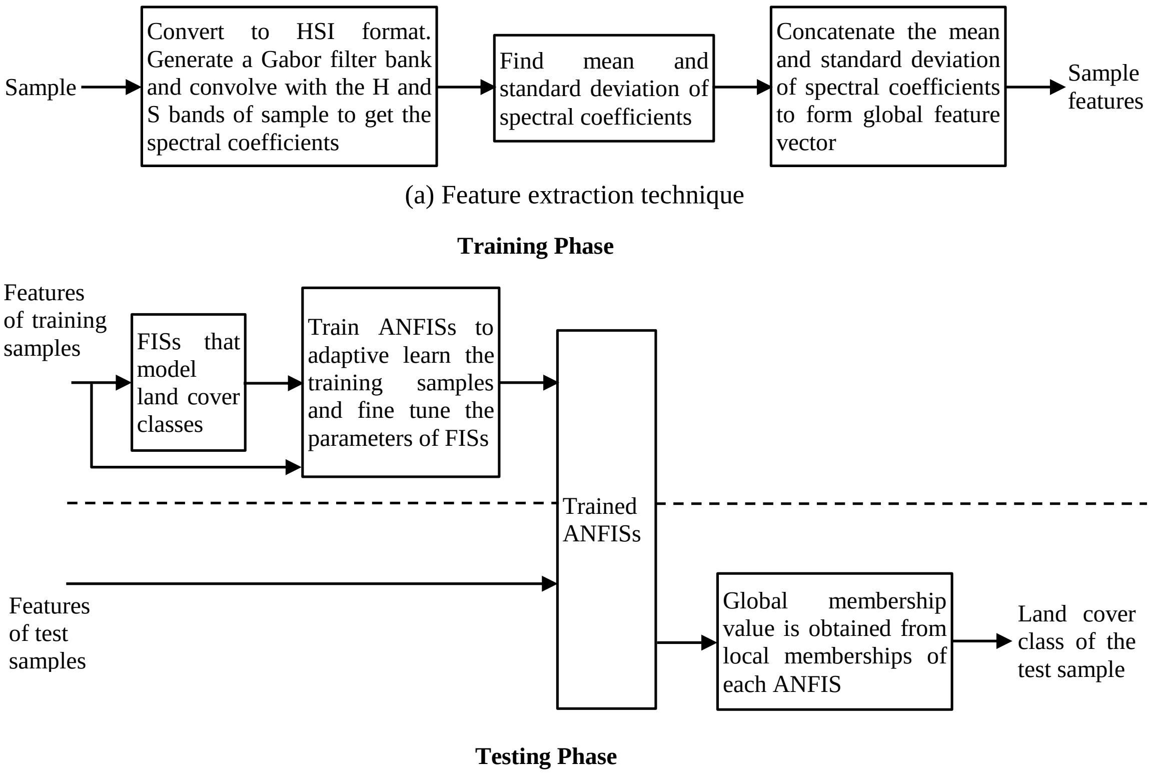
1.1 RELATED WORK

Many spectral features have been proposed in literature for texture analysis. Algorithms using wavelet transform [1] and rotation invariant features of Gabor wavelets [3] were developed for performing texture segmentation of gray level images and it was reported that the results were promising. Three kinds of features like energy computed from wavelet decomposed image, gray level feature and edge feature [2] were used in Synthetic Aperture Radar (SAR) image segmentation. Acharyya and Kundu [4] used M-band wavelet packet transform for feature extraction of IRS 1A and Spot remotely sensed images. A comparison of wavelet, Gabor and curvelet [5] was performed for face recognition under expression and illumination changes. It was reported that the coarse layer of curvelet and wavelet were found suitable for expression changes while the detail layer of curvelet was found suitable for illumination changes. Two-dimensional Gabor wavelet was used in detecting edges, corners and blobs [6]. Dorsal hand vein recognition [7] was performed using 2D Gabor features and normalised Hamming distance metric. It was reported that when trained with sufficient dorsal hand vein images, high recognition rate (>99%) was obtained.

Many classification algorithms are used in literature. Shing and Jang [8] proposed and defined ANFIS as a fuzzy inference system implemented in the framework of adaptive network. Nedeljkovic [9] inferred that the supervised classification of remotely sensed images could be performed with fuzzy classifiers and the classification accuracy obtained was better than the pixel based classifiers like maximum likelihood classifier. Inan et al. [10] used wavelet features and ANFIS for classification of EEG signals. The supervised, unsupervised and semi supervised classification of remotely sensed images was performed with several fuzzy classifiers [11] and promising results were obtained. It is recorded thereof that fuzzy based classifiers [12] are fast and the accuracy depends on the type of member function used to model the input features. ANFIS aided by K-Means Classifier [13] was used for information extraction from river images with forest and sand distribution along its banks. The silhouette of the moving object in a video frame was detected by building a time-varying fuzzy background model [14]. The experiments proved that the developed approach was better than the classical approach. Rajesh et al. [15] performed land cover classification using wavelet packet transform and ANFIS which performed better than the classical classifiers.

The grey level co-occurrence matrix (GLCM) texture measure and the maximum likelihood classification approach were used for classification of IKONOS imagery [16] using three datasets such as a spatial, spectral and combined dataset. The experimental results proved that the combination dataset produced a high classification accuracy of 86.1%. Colour GLCM [17] measure was introduced by Benčo and Hudec for colour texture classification. Colour GLCM texture measure is a row vector of 9 homogeneity values found for the 9 co-occurrence matrices obtained from the 9 cross relations of 3 bands.

From the texture based methods mentioned earlier, it is observed that texture feature extraction using Gabor wavelet has been one of the promising approaches. It is likely that incorporating fuzziness can improve the classification accuracy of pattern classification problems. Motivated by this, it is planned to use a fuzzy classifier with Gabor wavelet for land cover classification. ANFIS is a fuzzy classifier used in classification and validation of classified result. In ANFIS based classification approach, initially the training patterns are modeled as a FIS and subsequently through neural network learning, the FIS parameters are fine tuned to classify test patterns. Justified by these facts, Gabor wavelet is combined with ANFIS in performing land cover classification of remotely sensed images. The objective of the research work is to use Gabor wavelet for feature extraction and propose a land cover classification algorithm for remotely sensed images using ANFIS.



(b) Classification

Fig.1. Feature extraction and classification

The paper is organized as follows. Section 2 describes the outline of the proposed approach, Gabor wavelet feature extraction and proposed algorithm for land cover classification with ANFIS classifier. Section 3 describes the experimental data, the experiments conducted, results obtained and performance evaluation. The final section draws conclusion.

1.2 OUTLINE OF THE PAPER

The proposed approach has texture feature extraction part as shown in (Fig.1(a)) and classification part as shown in (Fig.1(b)). For extracting features, the sample is converted to HSI (Hue, Saturation and Intensity) format. The H and S bands of sample are convolved with the Gabor filter bank to get spectral coefficients. The mean and standard deviation of spectral coefficients are concatenated into a global feature vector to characterise the global features of the sample. The ANFIS classifier works in two phases as shown in (Fig.1(b)). In the training phase marked in the upper half of (Fig.1(b)), the training samples are extracted from distinct land cover classes of remotely sensed image. Each land cover class is modeled by a FIS. The global features of the training samples are given as input to each FIS which in turn uses an ANFIS to adaptively learn the features of the training samples. In the testing phase marked in the lower half of (Fig.1(b)), test samples centered around each pixel of remotely sensed image are extracted, global features are found and given as input to trained ANFISs. Each trained ANFIS gives a local membership value. The local membership values are combined into a single global membership value using a simple relation (such as finding maximum from local membership values) that decodes the land cover class of the test sample.

2. TEXTURE FEATURE EXTRACTION USING GABOR WAVELET

Gabor wavelet transform can break up a signal into its frequency components. The 2D Gabor wavelet filter can be represented as a complex sinusoidal signal modulated by a Gaussian kernel function. It is capable of down sampling an image to desired number of scales and orientations. Texture features obtained using Gabor wavelet are translation and rotation invariant. If $f(x, y)$ is the gray level distribution of an image of size ($M \times N$), then the convolution of image $f(x, y)$ and a Gabor kernel ($g(x, y)$) is performed to get augmented Gabor feature vector $f'(x,y)$ as in Eq.(1).

$$f'(x,y) = f(x,y) * g(x,y) \tag{1}$$

If a Gabor filter bank with 'a' scales and 'b' orientations is used, after convolution with the image we get Gabor coefficients represented as $f'_{11}(x,y)$,….., $f'_{ab}(x,y)$. The texture features are obtained by finding statistical features like mean (μ) and standard deviation (σ) of Gabor coefficients ($f'(x,y)$) using Eq.(2) and Eq.(3).

$$\mu = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} f'(x,y) \tag{2}$$

$$\sigma = \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\left(f'(x,y)-\mu\right)^2} \tag{3}$$

The texture features obtained are concatenated to form the feature vector. In the remotely sensed image, the feature vectors of '*H*' and '*S*' bands, $Gabor_H$ and $Gabor_S$ are concatenated to obtain its global feature vector, $Gabor_{global}$ which can be represented as given below.

$$Gabor_H = [\mu_{11}, \sigma_{11}, \ldots, \mu_{ab}, \sigma_{ab}]_H \quad (4)$$

$$Gabor_S = [\mu_{11}, \sigma_{11}, \ldots, \mu_{ab}, \sigma_{ab}]_S \quad (5)$$

$$Gabor_{global} = [Gabor_H, Gabor_S] \quad (6)$$

3. PROPOSED LAND COVER CLASSIFICATION ALGORITHM USING ANFIS CLASSIFIER

The real contribution of the research work lies in the methodology adapted for land cover classification. In previous papers [15], a global approach as stated below is adapted. The remotely sensed image as a whole will be convolved with the Gabor filter bank to get spectral coefficients. In order to classify each pixel of the remotely sensed image, the statistical features of local neighbourhood of the whole image will be compared with the statistical features of equally sized training samples. In this paper, in contrast to the global approach, a local approach is adapted. Here Gabor filter bank is made to convolve with the local neighbourhood of the whole image and statistical features are obtained. During classification, these statistical features are compared with the statistical features of equally sized training samples. The merit of this local approach is that it helps in achieving scalability issue of big data. As the tasks associated in classifying each pixel have become independent, the algorithm can be parallelized. The sequential algorithm for land cover classification of remotely sensed images using Gabor wavelet and ANFIS is proposed in this article and listed below.

Training Phase:

Step 1: Find global feature vectors of training samples.

Step 2: Each land cover class is modeled using a FIS.

Step 3: The training set for the respective FIS is formed as follows. The global feature vectors of all training samples (found using the procedure described in Section 2.2) are concatenated row wise. In the last column, the class labels of the training samples belonging to the respective land cover class are entered as one while others are entered as zero.

Step 4: Gaussian member functions are used to model the global features of training samples. The initial parameters of the Gaussian member functions are set from the statistics (μ and σ) computed in the training set.

Step 5: Later the parameters of each FIS are fine tuned with the help of an ANFIS (that uses least squares method in the forward pass and back propagation descent method in the backward pass) to reflect the input output relationship of training patterns in the training set. The working principle of ANFIS is shown in (Fig.2). Thus ANFIS completes learning the training samples.

Testing Phase:

Step 6: Extract a test sample from the input remotely sensed image.

Step 7: Find global feature vector of test sample.

Step 8: The global feature vector of the test sample is given as input to all trained ANFIS's.

Step 9: The class label of the test sample equals the class label of the ANFIS that returned maximum membership value.

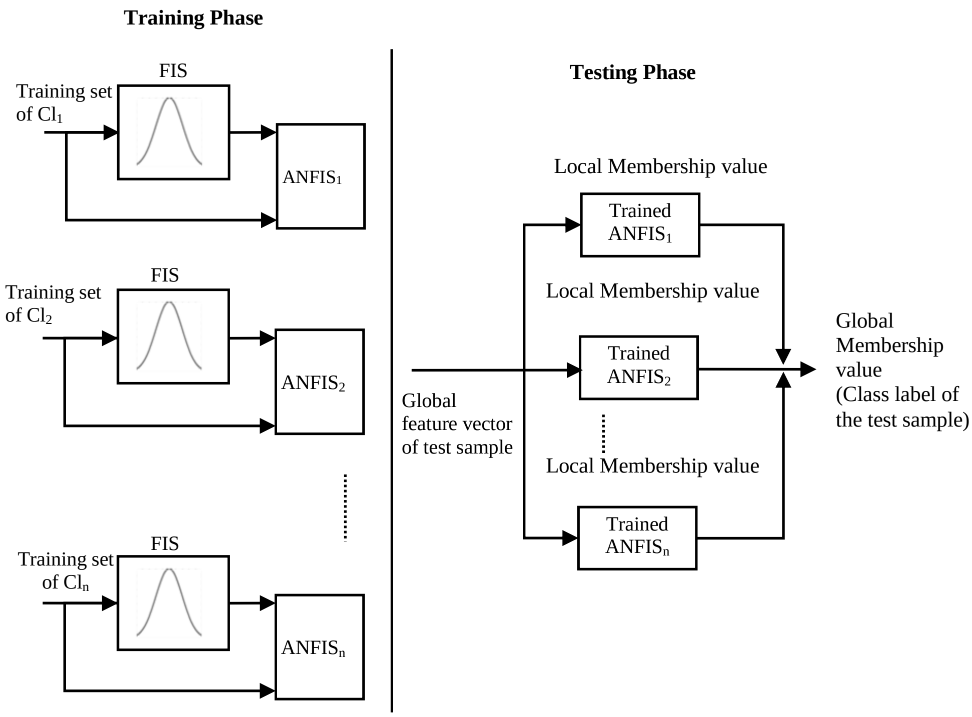


Fig.2. Working Principle of ANFIS

The detailed pseudo code for the algorithm is listed below.

```
% Let there be 5 land cover classes.
% Let 'q' be the number of training samples each of size (16 × 16).
% Convert the remotely sensed image and all the training samples from % RGB to HSI color space.
FOR i = 1: 5
    FOR j = 1: q
        READ training_sample{i, j}
        temp = training sample{i, j}
        % Separate H and S bands of 'temp'.
        h1= temp(:,:,1);
        s1= temp(:,:,2);
        % Compute Gabor features H and S bands of
        % training sample
        temp1 = CALL SUB Gabor_Features(h1)
        temp2 = CALL SUB Gabor_Features(s1)
        temp3 = [temp1 temp2];
        Training_feature_Gabor{i,j} = {temp3};
    END
END
FOR i = 1: 5
        % Model each land cover class as a FIS
        % Form training set TR{i, :} of each land cover class 'i'
        % as follows.
        % First, concatenate the global features of all training
        % samples row-wise.
        tr = reshape(Training_feature_Gabor', [5*q 1]);
        % In each row, append 1 in the last column if the
        % training sample belongs to the respective land cover
        % class, otherwise append 0.
    IF i == 1
      Last_column_value = [ones(1,q) zeros(1,4*q)];
    ELSE IF i == 2
      Last_column_value = [zeros(1,q) ones(1,q) zeros(1,3*q)];
    ELSE IF i == 3
      Last_column_value = [zeros(1,2*q) ones(1,q)
                           zeros(1,2*q)];
    ELSE IF i == 4
      Last_column_value = [zeros(1,3*q) ones(1,q) zeros(1, q)];
    ELSE
      Last_column_value = [zeros(1,4*q) ones(1,q)];
      TR{i, :} = cat(2,tr, Last_column_value);
END
      % Generate FISs (in_fis1, in_fis2, ….., in_fis5) to model
      % the global features of the 5 land cover classes.
      % Let it be given as input to ANFISs that give out output
      % FISs (as out_fis1, out_fis2, ….., out_fis5).
epoch_n = 60;
in_fis1 = genfis1(TR{1},[3 3 3 3],
    char('gaussmf','gaussmf','gaussmf','gaussmf'), 'constant');
out_fis1 = anfis(TR{1},in_fis1,epoch_n,0);
in_fis2 = genfis1(TR{2},[3 3 3 3],
    char('gaussmf','gaussmf','gaussmf','gaussmf'), 'constant');
out_fis2 = anfis(TR{2},in_fis2,epoch_n,0);
in_fis3 = genfis1(TR{3},[3 3 3 3],
    char('gaussmf','gaussmf','gaussmf','gaussmf'), 'constant');
out_fis3 = anfis(TR{3},in_fis3,epoch_n,0);
in_fis4 = genfis1(TR{4},[3 3 3 3],
    char('gaussmf','gaussmf','gaussmf','gaussmf'), 'constant');
out_fis4 = anfis(TR{4},in_fis4,epoch_n,0);
in_fis5 = genfis1(TR{5},[3 3 3 3],
char('gaussmf','gaussmf','gaussmf','gaussmf'), 'constant');
out_fis5 = anfis(TR{5},in_fis5,epoch_n,0);
% read LISS IV remotely sensed image in HSV format as p
READ p
% Separate H and S bands of p
h = p(:,:,1);
s = p(:,:,2);
[m1 m2] = size(h);
FOR i = 1: m1
    FOR j = 1: m2
        im1 = Take 16×16 overlapping test sample in H band
        k1{i, j} =  CALL SUB Gabor_Features (im1)
        im2 = Take 16×16 overlapping test sample in S band
        k2{i, j} = CALL SUB Gabor_Features (im2)
        k3{i, j} = cat(2, k1{i,j}, k2{i,j})
    END
END
% convert k3 cell array to a matrix with the global features of
% each pixel arranged row wise one below the other.
temp = reshape(k3',[m1*m2 1]);
f15 = cell2mat(temp);
% Evaluate FISs to get local memberships
local_mem1 = evalfis(f15,out_fis1);
local_mem2 = evalfis(f15,out_fis2);
local_mem3 = evalfis(f15,out_fis3);
local_mem4 = evalfis(f15,out_fis4);
local_mem5 = evalfis(f15,out_fis5);
local_mem6 = evalfis(f15,out_fis6);
% Find global membership
t1 = [local_mem1 local_mem2 local_mem3 local_mem4 local_mem5 local_mem6];
[global_mem class] = max(t1, [], 2);
cl = reshape(class,[m1 m2]);
% Display the classified image
figure, image(cl)
% Subroutine for finding Gabor features
SUBROUTINE f = Gabor_Features(im)
    FOR u = 1:4
        f1(1,u) = Generate the Gabor wavelets
% Convolve image with Gabor wavelets
        gb = abs(conv2(im,f1{1,u},'same'));
```

```
% conversion of 2D feature into 1D feature
          f2{u} = im2col(gb',[16 16]);
   END
   l = [f2{1} f2{2} f2{3} f2{4}];
% Find mean and standard deviation
   m = mean2(l(:));
   s = std2(l(:));
   e = [m s];
   f = {e};
RETURN
```

4. EXPERIMENTS AND RESULTS

4.1 STUDY AREA AND DATA USED

The remotely sensed image under study is an IRS P6, LISS-IV image supplied by National Remote Sensing Centre (NRSC), Hyderabad, India. The image has been taken in July 2007 and is of size 1004×1158×3. It is formed by combining bands 2, 3 and 4 of LISS- IV data (Green, red and near IR) and is shown in (Fig.3). The remotely sensed image covers the area in the western part of Tirunelveli city located in the state of Tamil Nadu in India. The experimental classes or training samples shown in (Table.1) are the areas of interest extracted from source image in (Fig.3) and are of size 16×16.

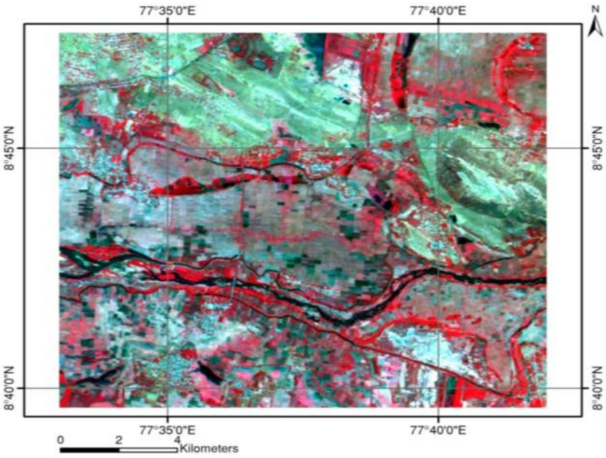


Fig.3. Remotely sensed image

Table.1. Training samples and their descriptions

Class No.	Actual Class	Sample Used	Description
C1	Vegetation-1		Thick cultivated vegetation
C2	Vegetation-2		Rice crops
C3	Settlement		Residential area
C4	Water		Water in rivers and tanks
C5	Soil		Barren land with sparsely and randomly scattered shrubs

4.2 PERFORMANCE METRICS

The overall classification accuracy and Kappa coefficient are the performance metrics for assessing the classified image. To compute these values, a confusion matrix of size ($c \times c$) is built from the classified image where 'c' is the number of classes. The overall classification accuracy (P_o) can be found as follows,

$$P_o = \frac{\sum_{i=1}^{c} x_{ii}}{m} \tag{7}$$

where, 'm' is the total number of observations and x_{ii} is the observation in row 'i' and column 'i' of confusion matrix. The classification accuracy expected (P_e) is found as below,

$$P_e = \frac{\sum_{i=1}^{c} x_1 x_2}{m^2} \tag{8}$$

where x_1 is the marginal total of row 'i' and x_2 is the marginal total of column 'i'. Kappa coefficient is found using P_o and P_e as follows,

$$\text{Kappa Coefficient} = \frac{P_o - P_e}{1 - P_e} \tag{9}$$

4.3 EXPERIMENT: LAND COVER CLASSIFICATION OF REMOTELY SENSED IMAGE WITH GABOR WAVELET AND ANFIS CLASSIFIER

It is aimed to achieve high classification accuracy and so the sample size is fixed to a minimum of (16×16). Gabor wavelet down sampling was performed up to one scaling level as the sample size is small. Within the scale, features were extracted from samples in four orientations such as 90, 180, 270 and 360 with a mean phase shift of $\pi/2$. The class labels of the test samples were found using ANFIS classifier. The classified image is shown in (Fig.4). In our experiments, a set of stratified random samples comprising 2400 pixels were used for building error matrix. The performance measures like classification accuracy and kappa coefficient described are found for the classified image in (Fig.4) and shown in (Table.2) and (Table.3) respectively.

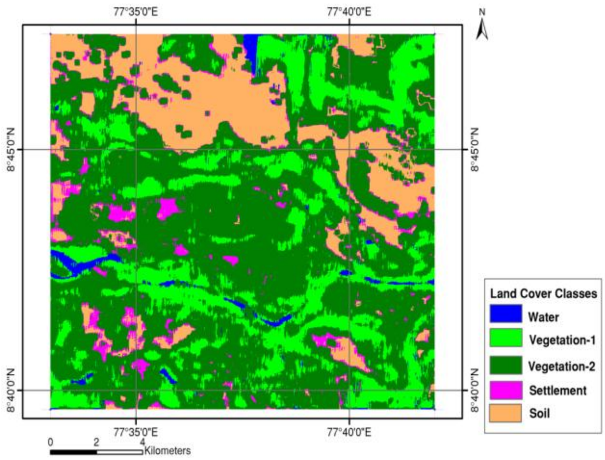


Fig.4. Classified image using proposed algorithm

Table.2. Confusion Matrix

	BG	C1	C2	C3	C4	C5	RoT
C1	0	260	23	1	0	0	284
C2	1	14	736	5	1	48	805
C3	0	16	15	300	0	8	339
C4	1	10	28	0	215	0	254
C5	1	0	0	1	0	716	718
CoT	3	300	802	307	216	772	2400

BG- Back Ground, RoT- Row Total, CoT- Cloumn Total

Table.3. Accuracy Totals

Class Name	RT	CT	NC	PA%	UA%
BG	3	0	0		
C1	300	284	260	91.55	86.67
C2	802	805	736	91.43	91.77
C3	307	339	300	88.50	97.72
C4	216	254	215	84.65	99.54
C5	772	718	716	99.72	92.75
Total	2400	2400	2205		
Overall Accuracy = 92.8%			**Overall Kappa = 0.943**		

RT- Reference Total, CT- Classified Total, NC- Number Correct, PA-Producer's Accuracy, UA-User's Accuracy

The classified image exhibits good texture discrimination between various classes. From (Fig.4.), it is inferred that a small fraction of water pixels have been misclassified to Vegetation-2 class and some others belonging to Vegetation-1 class have been misclassified to Vegetation-2 class.

4.4 EXPERIMENT: PERFORMANCE EVALUATION OF PROPOSED ALGORITHM

For evaluating the performance of the proposed algorithm with the existing texture based algorithms, ANFIS was combined with wavelet and color GLCM and the results are shown in (Table.4).

Table.4. Performance comparison of proposed algorithm

Name of the feature extraction technique	Overall classification accuracy (%)	Overall Kappa coefficient
Gabor Wavelet	92.8	0.943
Color GLCM	80	0.7062
Wavelet	85.17	0.8074

It is customary in GLCM to use two statistical measures, one orderliness measure and one contrast measure for getting good pattern discrimination. In color GLCM, to reduce computational complexity involved in processing a large vector, only homogeneity (contrast group measure) measures are considered. So color GLCM produced 80% classification accuracy. Gabor wavelet extracts texture features not only at different scaling levels like wavelet, but also at different rotational angles. So the proposed algorithm using Gabor wavelet performs better and gives a high classification accuracy of 92.8%.

5. DISCUSSION AND CONCLUSION

The land cover classification algorithm of remotely sensed image using Gabor wavelet and ANFIS classifier is proposed in this article. The challenge associated with ANFIS is that the classification accuracy drops when the mean and standard deviation values of land cover classes overlap. In order to override the challenge, sufficient training samples were given to train each ANFIS. Furthermore, ANFIS was trained with optimal number of epochs to reduce misclassifications. The challenge associated with the global approach used in earlier work on Gabor filter based classification is that as the size of the remotely sensed image increases, the size of the spectral coefficients generated also increases proportionately which in turn increases the requirement of storage space. During implementation, this storage overhead causes a heavy stress to the programmer. The local approach adapted in the proposed sequential algorithm not only overcomes the drawback but leaves a gap for exploiting task level parallelism. From the experiments, it is proved that the proposed algorithm yields 92.8% classification accuracy and outperforms other existing texture based algorithms taken for study based on error matrix, classification accuracy and kappa statistics.

In future, it is proposed to modify the sequential algorithm to parallel algorithm for improving performance. It is also planned to extend the study to other transforms like curvelet, bandelet, contourlet and ridgelet.

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