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UNSUPERVISED IMAGE CLASSIFICATION BY RADIAL BASIS FUNCTION NEURAL NETWORK (RBFNN)

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ABSTRACT: This work extends the application of Radial Basis Function (RBF) neural network for the unsupervised classification of images. The *radial basis function (RBF) network* enables non-linear transformation followed by linear transformation to achieve a higher dimension in the hidden space. If classification is done in a high dimensional space, it is more likely to be linearly separable as compared to that in low dimensional space. This is directly related to the capacity of the network to approximate a smooth input-output mapping. A radial basis function like a spherical Gaussian, is a function that is symmetrical about a given mean or center point in a multi-dimensional space. Radial Basis function Neural Network (RBFNN) is a general regression technique, which is suitable for both function mapping and classification problems. Initially random centers were generated and then the final ones were calculated using the k-means clustering algorithm. The RBF Network has been implemented on IRS 1C LISS-3 image of Kanpur and adjoining regions, India.

1. INTRODUCTION

Multispectral classification of images is gaining importance in remote sensing. These images are being extensively used, particularly for vegetation, land-use, precision farming and urban studies. Classifying multisource remote sensing and spatial data requires the ability to match large volumes of input pattern data simultaneously to generate categorical information as output. Since the learning and recall depend on the linear and nonlinear combination of data patterns instead of the statistical parameters of the input data, neural networks offer the opportunity to analyze spatial data with different origins and properties simultaneously, without *a priori* assumptions about the distribution for each data type. In fact, neural networks have the ability to learn those distributions, if they exist, in the input data. Therefore, a neural network can be trained by data from different sources. The one, two, or perhaps more hidden layers consist of a number of processing elements which enable the translation of input data into output information, which, in the present context, is the land cover classification corresponding to an input pattern. Ideally, each data type will make a unique contribution to the discrimination of land cover class patterns, therefore, enabling the neural network to learn the spectral, spatial, and temporal signature of each class.

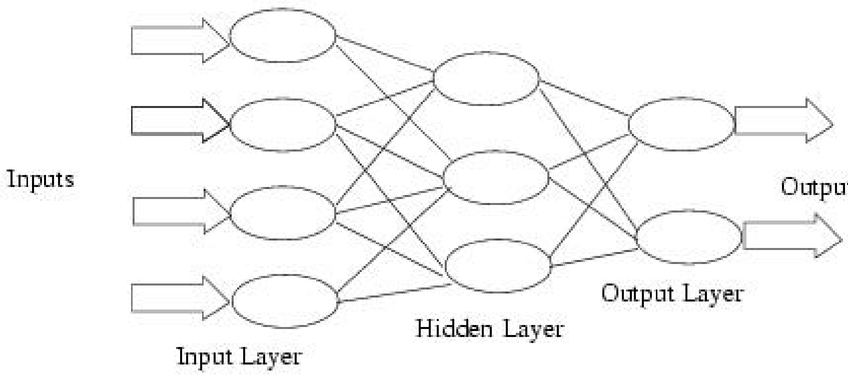

Figure 1: Schematic representation of generalized neural network

This paper discusses one of these methods (a neural network approach) to do classification (unsupervised) i.e.Radial Basis Function (RBF) Network.

2. RBF ALGORITHM

The construction of a *radial basis function (RBF) network*, in its most basic form, involves three layers with entirely different roles. The input layer is made of source nodes (sensory units) that connect the network to its environment. The second layer, the only hidden layer in the network, applies a non-linear transformation from the input space to the hidden space, in most applications the hidden space is of high dimensionality. The output layer is linear, supplying the response of the network to the activation pattern (signal) applied to the input layer. The radial basis function expansion for one hidden layer and an arbitrary radial basis function is represented by equation (1)

$$y_k(x) = \sum_{i=1}^{M} w_{ki}\, f_i(\mathrm{mod}(c_i - x)) \qquad (1)$$

where: y_k is the output vector, x is input vector, w_{ki} is weight from the i^{th} kernel node to the k^{th} output node, c_i is centroid of the i^{th} kernel node ,σ_i is bandwidth of the i^{th} kernel node and M is number of kernel nodes. $f_i = \exp(-\left\|(c_i - x)\right\| / 2(\sigma_I)^2)$ is Gaussian RBF with bandwidth of σ_i. The way involves using *k*-means clustering to determine the c_i, a *k*-nearest neighbor heuristic to determine the σ_i and multiple linear regressions to determine the w_{ki}. The *k*-means clustering algorithm finds a set of cluster centres and a partition of the training data into subsets. Each cluster centre is then associated with one of the *M* kernels or centres in the hidden layer. After the centres are established the width of each kernel is determined to cover the training points to allow a smooth fit of the desired network outputs. The width is selected so that σ_i is greater than the distance to the nearest kernel centre but also as small as possible to keep it's distance of influence to it's local region. An appropriate width can be computed by equation (2) using the *k*-nearest neighbour heuristic for 2 nearest neighbours, ie b=2.

$$\sigma_i = \sqrt{\frac{1}{b}\sum_{j=1}^{b}(\left\|c_i - n_j\right\|)^2} \qquad (2)$$

Here n_j is the *k*-nearest kernel centre vectors of c_i, and c_i is center of the i^{th} kernel node. As the network has only one layer of weighted connections and the output nodes are simple summation units, the training can be done by linear least squares estimation or by using a pseudo-inverse of the (M×N) matrix *G* giving all the outputs from the M radial basis functions f_i for a case of N example vector sets ie. M number of centres or kernel nodes where N is number of input output vector pairs, K is output vector dimension, W is unknown (K×M) weight matrix, G is the matrix of output vector set from the kernel layer (M×N) and T is matrix of target or desired vector set at the output (K×N) .The equation which needs to be solved is equation (3).

$$G=T \qquad (3)$$

The solution of this equation represents the minimum squared norm of the residuals, ie.

$$\min_{W} \left\|T - WG\right\|^2 \qquad (4)$$

And the solution is:

$$W = TG^T (GG^T)^{-1} \qquad (5)$$

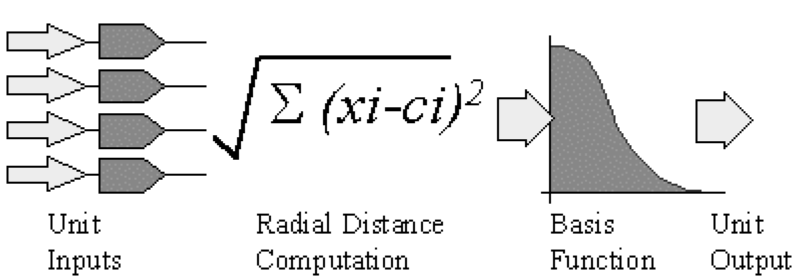

Figure 2: Schematic representation of Radial Basis Function (RBF) neural network

3. STUDY AREA

The resample image of Kanpur, Unnao and parts of other adjoining districts of Uttar Pradesh, India has been used for classification. The area falls between 26° 5′24″ and 26°43′21″(North) latitude and 79° 55 ′53″ and 80°45′20″(East) longitude

4. METHODOLOGY

A IRS-1C LISS-3 image has been used as the test data. The number of bands_considered are K=3 (viz. band no.2, 3,4). An n example feature pixel vectors x1, x2,..., x_N are considered. If M be the number of representative, K*M centers are generated randomly. Each pattern is assigned to its closest cluster center by calculating the Euclidean distance between the input vector image and each cluster center in K dimensional space. The new centers are generated by calculating the mean of each cluster again. The above process continues till the cluster centers are almost, within a required degree of accuracy, which is 1 in this case. Radial Basis Function outputs are calculated for the input training image to form the transformation image matrix G. The weight matrix is then computed. Target classified image matrix is finally obtained by multiplication of test image matrix to weight matrix.

5. RESULTS

The classified image obtained after unsupervised classification using RBFNN is shown in Figure 4. Accuracy analysis of the classification has been done by calculating the overall accuracy and kappa statistics of the classification. The confusion matrix of the classified image w.r.t the reference supervised classification image is shown in Table 1.

Table 1: Confusion Matrix between classified images generated by Maximum Likelihood Classification and Classification by RBF neural network respectively

	W	D	C	H	L	U	Wl	s	Σ_x
W	14640	33450	0	1	0	0	2327	0	50418
D	3439	868340	58416	8022	18222	127324	2823	0	1086586
C	8665	191726	338123	29916	140213	317743	12162	8522	1047070
H	0	0	0	55491	79487	373445	32856	43748	585027
L	0	0	0	2140	240606	44606	1431	0	288783
U	445	528068	70884	116780	196762	2195790	8664	0	3117393
WL	34	987	95	542	8767	654	6556	764	18399
S	65	876	565	91	654	8765	765	7665	19446
Σ_y	27288	1623447	468083	212983	684711	3068327	67584	60699	

Accuracy of a reference class = x_{ii}/Σ_{yi}
Accuracy of the class (form unsupervised classification) = x_{ii}/Σ_{xi}
The accuracy of respective classes is depicted in Table 2.

Table 2: %age accuracy of the various classes for both unsupervised classified image and supervised classified image

Class	Unsupervised Classification Accuracy(Producer's Accuracy, in %)	Supervised Classification Accuracy(User's Accuracy, in %)
W[♦]	53.65	29.03
D	53.48	79.91
C	72.23	32.29
H	26.05	9.48
L	35.14	83.31
U	71.56	70.43
WL	9.7	35.63
S	12.62	39.41

Overall accuracy $=\Sigma x_{ii}/\Sigma(\Sigma_{yi})$ = 16153455/26931402 =59.98%

[♦] W is Water, D is dense vegetation, C is cultivation, H/L is High/Low density urban, WL is waste land, S is sand, U is undefined.

The accuracy assessment can also be done by a discrete multivariate analysis called Kappa statistics.

$$K = \frac{N\sum_{i=1}^{n} x_{ii} - \sum_{i=1}^{n}(x_{i+}x_{+i})}{N^2 - \sum_{i=1}^{n}(x_{i+}x_{+i})} \qquad (6)$$

where n is the number of rows in the matrix,x_{ii} is the number of observations in row i and col. i and x are the totals of row i and column i respectively and N is the total number of observations. Putting the values in equation (6) we get Accuracy K = 422889697600/737449760600 = 57.34 % .The accuracy results by the two aforesaid methods are different because the information given from both the analysis is different. The overall accuracy only incorporates the major diagonal of the confusion matrix but the later also incorporates the off diagonal elements as the product of row and column.

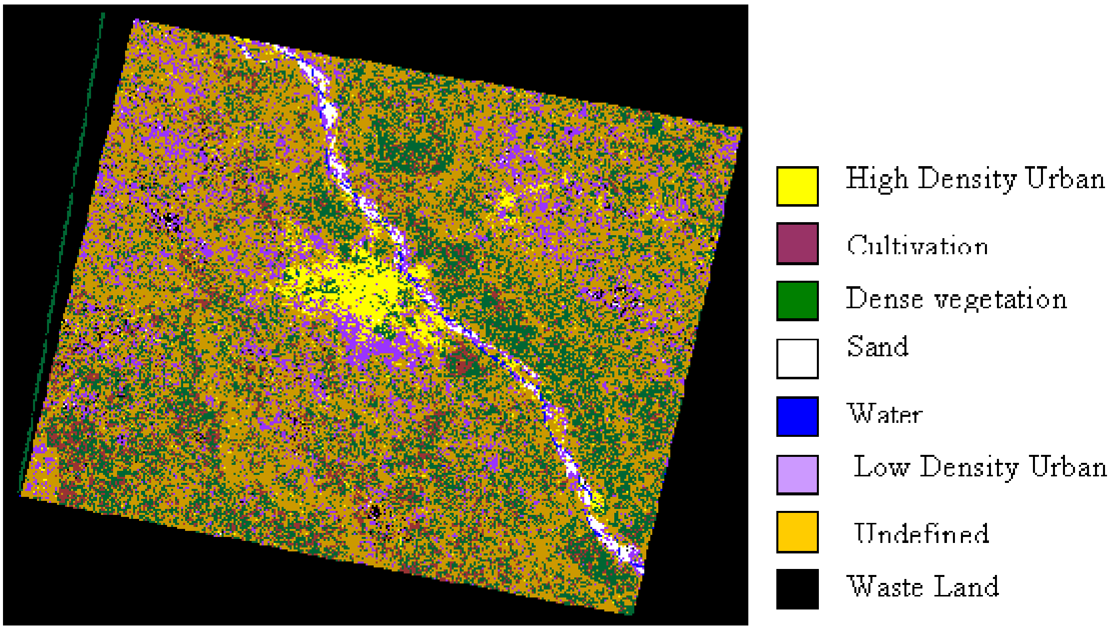

Figure 3: Supervised Maximum Likelihood Classified Image

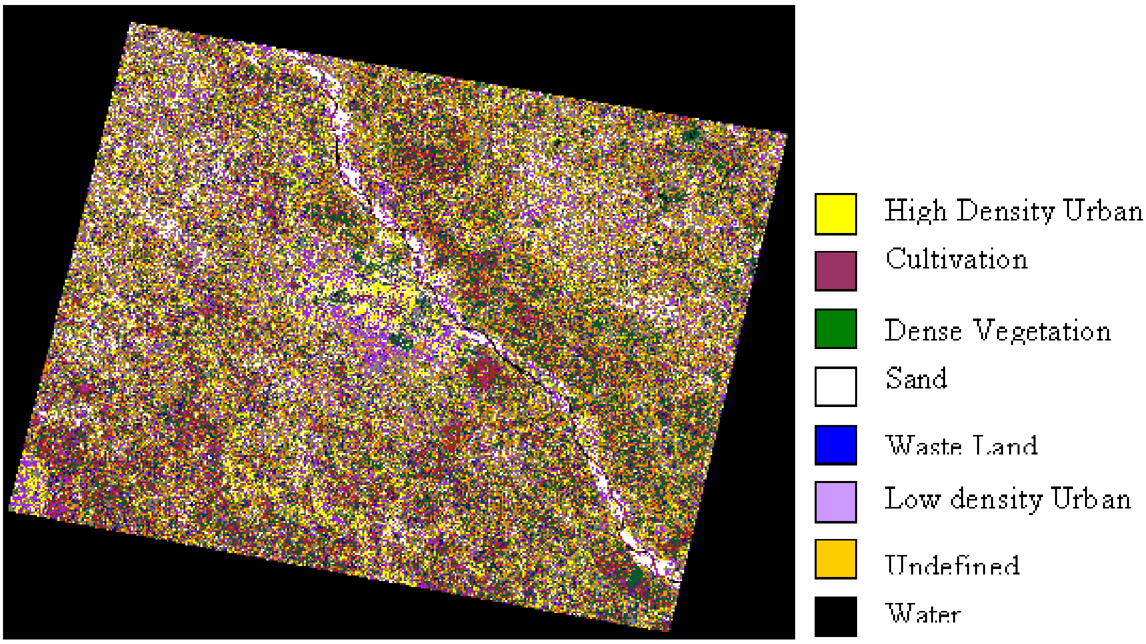

Figure 4: Unsupervised (RBFNN) classification image

6. CONCLUSION

The RBFNN is a effective way of unsupervised classification of images. It recognizes the regions that do not fall in any class quite successfully because it uses non-monotonic transfer function based on Gaussian density approach. More so these are capable of approximating nonlinear relationships effectively. Also the training time of the network is quite small. Though the classification accuracy obtained by this method is good, in comparison to other artificial neural network strategies, however even now the accuracy is not sufficient for this being used for detailed information extraction. Neural network models tested which incorporated multidate ancillary spatial information had accuracies of approximately 9-12 percent greater than single date neural networks (4). Incorporating the possibility of linear relations (accompanied with nonlinear one) in the network and increasing the number of centers can be useful for achieving better results.

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