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PERFORMANCE EVALUATION OF DISTANCE MEASURES IN PROPOSED FUZZY TEXTURE MODEL FOR LAND COVER CLASSIFICATION OF REMOTELY SENSED IMAGE

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Abstract
Land cover classification is a vital application area in satellite image processing domain. Texture is a useful feature in land cover classification. The classification accuracy obtained always depends on the effectiveness of the texture model, distance measure and classification algorithm used. In this work, texture features are extracted using the proposed multivariate descriptor, MFTM/MVAR that uses Multivariate Fuzzy Texture Model (MFTM) supplemented with Multivariate Variance (MVAR). The K_Nearest Neighbour (KNN) algorithm is used for classification due to its simplicity coupled with efficiency. The distance measures such as log likelihood, Manhattan, Chi squared, Kullback Leibler and Bhattacharyya were used and the experiments were conducted on IRS P6 LISS-IV data. The classified images were evaluated based on error matrix, classification accuracy and Kappa statistics. From the experiments, it is found that log likelihood distance with MFTM/MVAR descriptor and KNN classifier gives 95.29% classification accuracy.

Keywords:
Land Cover Classification, Kullback Leibler, Log Likelihood, Chi Squared, Bhattacharyya

1. INTRODUCTION

Texture based methods are widely used in applications like face recognition, content based image retrieval, pattern classification in medical imagery and land cover classification of remotely sensed images. Land cover refers to the biophysical attributes of the surface of the earth. Features of land covers include texture, shape, colour, contrast and so on. Land cover classification involves classifying the multispectral remotely sensed image into various land covers such as land, vegetation, water, etc. Texture is a surface property that characterizes the coarseness and smoothness of land covers. Pixel based techniques classify a pixel depending on the intensity of the current pixel but texture based techniques classify a pixel based on its relationship with the neighborhood. Texture measures can capture micro as well as macro patterns as they can be captured by varying the size of neighborhood. Recent texture based studies reveal that texture measures augmented with a contrast measure characterizing the local neighborhood yield accurate results. It is also observed from literature [2] that texture features are quite suitable for land cover classification of remotely sensed images and give high classification accuracy. The choice of feature extraction technique, distance measure and the classification algorithm is a challenging task in land cover classification.

The multivariate texture descriptor, *MFTM* is proposed for feature extraction in this paper. It combines the advantages of texture and fuzzy logic. The relationship of each neighbour pixel with the center pixel is expressed as a fuzzy membership value. The fuzzy membership values are consolidated to a single value called *MFTM* to characterize the pattern in the neighbourhood. Along with *MFTM*, Multivariate variance (*MVAR*) is used as a supplementary feature.

A distance measure should magnify the pattern differences that exist between different textures. A distance measure keeps dissimilar patterns apart with maximal distance and similar patterns together with minimal distance. It reduces classification error and helps in effective classification. In this paper, the KNN (K-Nearest Neighbour) classifier is used for performing classification of remotely sensed image. The advantage of KNN over other classifiers is that KNN is computationally simple and fast in discriminating various land covers. The objective of the research work is to conduct performance evaluation of distance measures such as log likelihood, Kullback Leibler, Chi squared, Manhattan and Bhattacharyya with KNN and proposed multivariate descriptor *MFTM* / *MVAR* in performing land cover classification of remotely sensed images.

1.1 MOTIVATION AND JUSTIFICATION OF THE PROPOSED APPROACH

A variety of texture descriptors are found in literatures. Local Binary Pattern (LBP) texture descriptor plays an important role in classification of texture images. The classification accuracies of LBP [1] and its derivatives were found suitable in many applications. In Multivariate Local Binary Pattern [2], nine pattern units incorporating cross relations between bands were added to form the feature vector of the colour image. To provide better pattern discrimination, Advanced Local Binary Pattern [3] was developed where the single minimum value obtained through applying repeated left circular shift operation on LBP pattern unit, was used as a texture descriptor. A new algorithm using Hidden Markov Model [4] was formulated for co-segmentation and analysis of 3D-MRI and MRSI data. In our earlier work, we did a comparative study [5] of texture descriptors for segmentation of gray level images and later proposed Modified Multivariate Local Binary Pattern (MMLBP) for classification of remotely sensed images. Local Texture Pattern (LTP) [6] was developed for gray level images and later extended to remotely sensed images as Multivariate Local Texture Pattern (MLTP) [7]. Dominant Local Binary Pattern [8] uses histograms of dominant patterns for pattern description. Local Derivative Pattern [9] captures pattern unit in different angles. A novel face descriptor named Local Color Vector Binary Pattern (LCVBP) [10] was introduced for face recognition to meet face images with challenges. Two colour local texture features like color local Gabor wavelets (CLGWs) and color local binary pattern (CLBP) [11] were developed for face recognition and both were combined to maximize their complementary effect of colour and texture information respectively. The Fuzzy Local Binary Pattern (FLBP) [12] descriptor was developed for texture characterization of B scan ultrasound images. The Fuzzy Local Texture Pattern (FLTP) [13] uses a fuzzy member function for pattern description. In FLBP [12] and FLTP [13], it is emphasized that the fuzzy based models perform better than their basic models.

Several distance measures are found in literatures. Bhattacharyya distance was proposed as a measure of divergence between two probability distributions by Bhattacharyya [14]. Shannon's concept of information-theoretic entropy and its generalisation known as the Kullback and Leibler [15] relative entropy or the divergence measure between two probability distributions has been used in several texture based applications. Ojala et.al used Kullback Leibler (KL) [16] distance for texture based classification of standard textures. Later, they used G Statistics log likelihood distance measure [17] as dissimilarity measure for comparing two one dimensional histograms representing feature vectors. Sokal and Rohlf proposed many statistical measures [18] for classification. Puzicha et al. proposed and examined nonparametric statistical tests [19] to define similarity and homogeneity measures for textures. Rubner et al. conducted an empirical evaluation of dissimilarity measures [20] for colour and texture information and concluded that the selection of distance measure was dependent on the application under consideration. We conducted an empirical evaluation of distance measures [21] for texture classification of remotely sensed images using Modified Multivariate Local Binary Pattern and concluded that Bhattacharyya and Chi squared distances provide better pattern discrimination.

Many classification algorithms have been used in papers. Texture classification of remotely sensed images using Support Vector Machine (SVM) [22] was performed by Hermes et al. and the same using Relevance Vector Machine (RVM) classifier [23] was reported by Demir and Ertuirk. Turtinen et al. performed texture classification of gray level images using Self Organizing Map (SOM) [24]. Ojala et al. used KNN classifier [16, 17] for texture based classification in most of his papers. Lu and Weng performed a detailed survey of various classification algorithms [25] including pixel based, sub pixel based, parametric, non parametric, hard and soft classification algorithms. They summarized that the success of an image classification algorithm depended on the availability of high quality remotely sensed imagery, the design of a proper classification procedure and analyst's skills.

Among the various distance measures, it is observed from literature that log likelihood, Kullback Leibler, Bhattacharyya and Chi squared distances are used for performing texture based classification. Motivated by this, the performance evaluation of distance measures such as log likelihood, Kullback Leibler, Chi squared, Manhattan and Bhattacharyya was conducted with the proposed multivariate descriptor (*MFTM* / *MVAR*) on remotely sensed images. It is also expected that when a multivariate descriptor is combined with an effective distance measure, promising results can be obtained. Justified by this fact, the performance evaluation of distance measures on land cover classification of remotely sensed images was carried out.

1.2 OUTLINE OF THE PAPER

The proposed approach has fuzzy based texture feature extraction part as shown in Fig.1(a) and classification part as shown in Fig.1(b). During feature extraction, the neighbour pixels (around a center pixel) of each 3 × 3 neighbourhood of a training sample is given as input to Sugeno FIS for assigning discrete output levels. Later, the centre pixel is assigned a pattern label using the proposed local texture descriptor (*MFTM*) with the help of discrete output levels. Multivariate Local contrast variance (*MVAR*) is also used as a supplementary local feature descriptor. These two local descriptors are then used to form a 2D histogram of each training sample. The 2D histogram formed characterizes the global feature of the sample. The KNN classifier works in two phases as shown in Fig.1(b). In the training phase, texture features in the form of 2D histograms of training samples are stored in the training database. In the testing phase, test samples centred around each pixel of remotely sensed image are extracted; 2D histogram is found and given as input to the KNN classifier. The classifier returns the class label based on the global features of training samples stored in the training database.

1.3 ORGANIZATION OF THE CHAPTER

The second section gives a detailed description of the texture based feature extraction method employed, classification algorithm and a range of distance measures used. The third section describes the experimental data and setup along with their results and performance metrics. The fourth section discusses the outcomes of various experiments for performance evaluation. The fifth section draws conclusion.

2. METHOD

2.1 FEATURE EXTRACTION TECHNIQUE

In this section during feature extraction, the local descriptors of every pixel along with its neighbours are computed as local texture descriptor and local contrast variance. Then the global description of the image or sub image can be obtained by accumulating the occurrence frequencies of the proposed local texture descriptor and local contrast variance in a 2D histogram as described in subsection 2.1.4.

2.1.1 Fuzzy Texture Model (FTM)-Proposed Model:

The *FTM* texture model extracts local texture information from a neighbourhood in an image. Let us take a 3 × 3 neighbourhood where g_c , g_1 , … g_8 be the pixel values of a local region where the value of the centre pixel is g_c and g_1 , g_2 , … g_8 are the pixel values in its neighbourhood. The relationship between the center pixel and one of its neighbour pixels is described by discrete output levels as shown in Eq.(1) below:

$$P(g_i, g_c) = \begin{cases} 0 & \text{if } g_i < (g_c - n) \\ 1 & \text{if } (g_c - n) \le g_i \le (g_c + n) \\ 9 & \text{if } g_i > (g_c + n) \end{cases} \quad (1)$$

Here '*n*' is the threshold which is set to express the closeness of neighbour pixel with the centre pixel. A Sugeno FIS is used to fuzzify the discrete conditions and obtain discrete output levels. The three categories of closeness of neighbour pixel to center pixel (corresponding to three discrete output levels) are termed as Negative Low close (NL), Absolute High close (AH) and Positive Low close (PL). The three categories of input membership functions for Sugeno FIS are termed as f_{NL}, f_{AH}, and f_{PL} and are defined in Eq.(2)-Eq.(4).

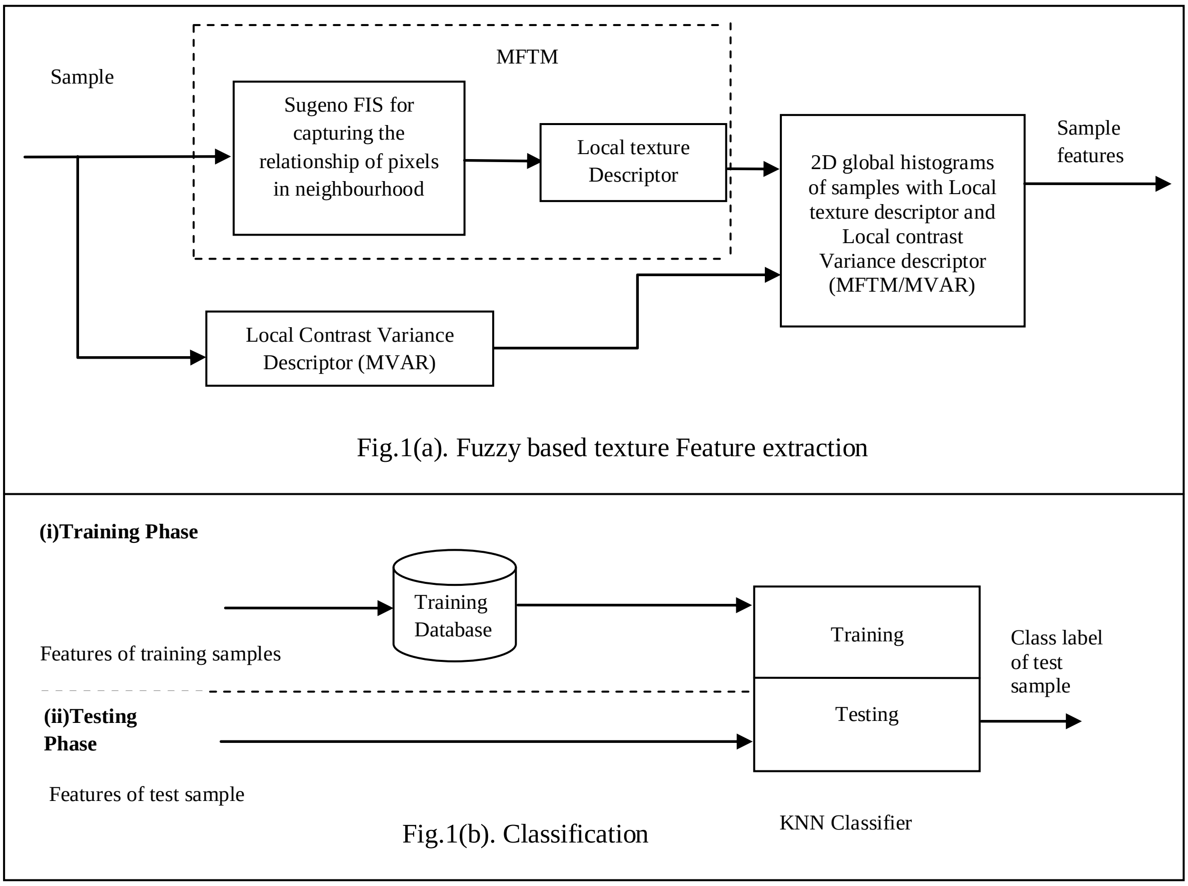


Fig.1(a). Fuzzy based texture Feature extraction

Fig.1(b). Classification

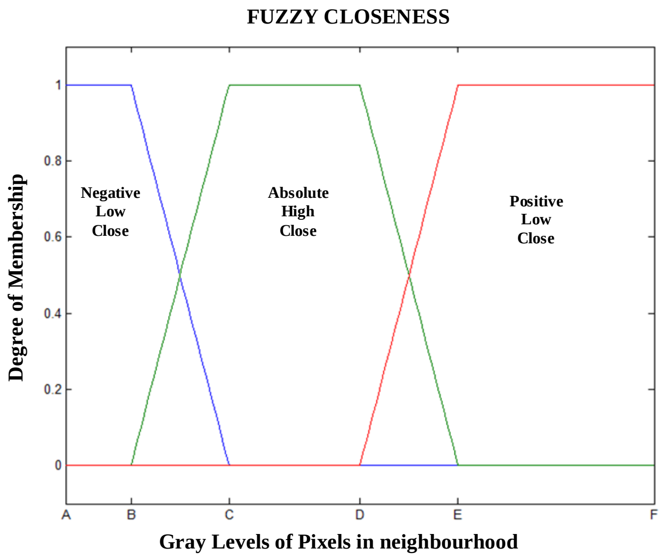
Fig.1. An overview of a) fuzzy based texture feature extraction and b) classification

$$f_{NL}\left(x, g_{\min}, g_{\min}, g_c - n, g_c - 2n/5\right) = \begin{cases} 0 & x \le g_{\min} \\ \dfrac{x - g_{\min}}{g_{\min} - g_{\min}} & g_{\min} \le x \le g_{\min} \\ 1 & g_{\min} \le x \le \left(g_c - n\right) \\ \dfrac{\left(g_c - 2n/5\right) - x}{\left(g - 2n/5\right) - \left(g_c - n\right)} & \left(g_c - n\right) \le x \le \left(g_c - 2n/5\right) \\ 0 & \left(g_c - 2n/5\right) \le x \end{cases} \tag{2}$$

$$f_{AH}\left(x, g_c - n, g_c - 2n/5, g_c + 2n/5, g_c + n\right) = \begin{cases} 0 & x \le \left(g_c - n\right) \\ \dfrac{x - \left(g_c - n\right)}{\left(g_c - 2n/5\right) - \left(g_c - n\right)} & \left(g_c - n\right) \le x \le \left(g_c - 2n/5\right) \\ 1 & \left(g_c - 2n/5\right) \le x \le \left(g_c + 2n/5\right) \\ \dfrac{\left(g_c + n\right) - x}{\left(g_c + n\right) - \left(g_c + 2n/5\right)} & \left(g_c + 2n/5\right) \le x \le \left(g_c + n\right) \\ 0 & \left(g_c + n\right) \le x \end{cases} \tag{3}$$

$$f\left(x, g_c + 2n/5, g_c + n, g_{\max}, g_{\max}\right) = \begin{cases} 0 & x \le \left(g + 2n/5\right) \\ \dfrac{x - \left(g + 2n/5\right)}{\left(g_c + n\right) - \left(g_c + 2n/5\right)} & \left(g_c + 2n/5\right) \le x \le x\left(g_c + n\right) \\ 1 & \left(g_c + n\right) \le x \le g_{\max} \\ \dfrac{g_{\max} - x}{g_{\max} - g_{\max}} & g_{\max} \le x \le g_{\max} \\ 0 & g_{\max} \le g_{\max} \end{cases} \tag{4}$$

The gray levels in neighborhood can fall under one of the three categories based on its membership values to the input fuzzy member functions as shown in Fig.2 below.



A = g_{min}, B = g_c-n, C = g_c - 2n/5, D = g_c + 2n/5, E = g_c + n and F = g_{max}

Fig.2. Assignment of three output levels with fuzzy conditions

Since we use a zero order Sugeno FIS, the output function is $z = c$ ($z = ax + by + c$ where $a = b = 0$) where c is a constant. So once the sugeno FIS is parameterised, for a given input pixel value in the neighbourhood, we can get one of the four constant discrete output levels through defuzzification based on the fuzzy rules listed below.

- If Gray Levels of Pixels in Neighbourhood is Negative Low close then (Output Level is 0)
- If Gray Levels of Pixels in Neighbourhood is Absolute High close then (Output Level is 1)
- If Gray Levels of Pixels in Neighbourhood is Positive Low close then (Output Level is 9)

The output levels characterize neighbourhood pixel relation. So, concatenation of these levels in a neighbourhood gives us a pattern unit. A sample calculation of pattern unit for n = 5 is shown in Eq.(5) below.

$$\begin{bmatrix} 206 & 194 & 201 \\ 203 & 201 & 198 \\ 212 & 210 & 202 \end{bmatrix} \rightarrow \begin{bmatrix} 9 & 0 & 1 \\ 1 & & 0 \\ 0 & 9 & 1 \end{bmatrix} \rightarrow 9\ 0\ 1\ 0\ 1\ 9\ 0\ 1 \qquad (5)$$

The pattern unit with discrete output levels is used to form a unique value to characterize the pattern in the chosen 3 × 3 local region. A uniformity measure (U) is introduced as defined in Eq.(7). It corresponds to the number of circular spatial transitions between output levels like 0, 1 and 9 in the pattern unit. Patterns for which U value is less than or equal to three are considered uniform and others are considered non uniform patterns. The gray scale FTM for 3 × 3 local region is derived as in Eq.(6). The sum of all discrete output levels is found for each possible uniform pattern and a unique FTM value is obtained from the lookup vector 'L'.

$$FTM = \begin{cases} L(S) & U <= 3 \\ 46 & Otherwise \end{cases} \qquad (6)$$

where, $S = \sum_{i=0}^{7} P(g_i, g_c)$ and

$$U = \left|s(g_7 - g_c) - s(g_0 - g_c)\right| + \sum_{z=1}^{7} \left|s(g_z - g_c) - s(g_{z-1} - g_c)\right| \qquad (7)$$

where, $$s(x,y) = \begin{cases} 1 & \text{if } |x - y| > 0 \\ 0 & \text{if otherwise} \end{cases}$$

The lookup vector (L) can be generated with the pseudo code listed below.

```
INITIALIZE L (0:72) = 0
SET Pattern Label (m) =1
Generate 38 possible pattern units
   FOR each pattern unit do
     Find uniformity measure (U)
           IF U <= 3
 Find sum of all discrete output levels in 'S'
                IF (L (S) == 0)
                            SET L (S) = m
                            INCREMENT m = m+1
                ENDIF
           ENDIF
    ENDFOR
```

The maximum possible sum in Eq.(6) is 72 as there can be eight 9's. So the size of the lookup vector is 73. Zero entries in the lookup vector show that those patterns will never occur. All other entries are entered sequentially starting from 1. The lookup vector has values in the range of 0 to 45 for all possible uniform patterns. So the value 46 is assigned for non uniform patterns.

2.1.2 Local Contrast Variance- Supplementary Feature:

Texture features by itself do not capture contrast information of an image. This will result in patterns with same texture values but different contrast values to get classified into same class. In order to avoid this, texture is supplemented with contrast information. Rotation invariant local variance is a powerful spatial property that provides contrast information and is defined for 3 × 3 neighbourhood of a gray scale image as follows.

$$VAR = \frac{1}{8}\sum_{i=1}^{8}(g_i - \mu_8)^2 \text{ where } \mu = \frac{1}{8}\sum_{i=1}^{8} g_i \qquad (8)$$

Equal percentile binning is performed for quantization of variance values. Then by using the formula '100 / B' where B is the required number of bins, we can find the bin interval for binning variance values.

2.1.3 Extending FTM and VAR for Multispectral Bands:

The proposed univariate FTM operator for gray scale image is extended as Multivariate FTM ($MFTM$). Among the multispectral bands, three most suitable bands for land cover classification are chosen and combined to form a RGB image. Nine FTM operators are calculated in the RGB image. Out of nine, three FTM operators describe the local texture in each of the three bands R, G and B individually. Six more FTM operators describe the local texture of the cross relation of each band with other bands (GR, BR, RG, BG, RB and GB). For example, the GR cross relation is obtained by replacing the centre pixel of R band in its neighbourhood with the centre pixel of G band. Nine *FTM* operators thus found are arranged in a 3 × 3 matrix. Then *MFTM* is found by calculating *FTM* for the 3 × 3 resulting matrix as shown below. This *MFTM* histogram has only 46 bins.

$$MFTM = FTM\begin{bmatrix} FTM^{RR} & FTM^{GR} & FTM^{BR} \\ FTM^{RG} & FTM^{GG} & FTM^{BG} \\ FTM^{RB} & FTM^{GB} & FTM^{BB} \end{bmatrix} \quad (9)$$

where, i ranges from 0 to 7 (Number of pixels in 3 × 3 neighbourhood), b_1 is the first band, b_2 is the second band and b_3 is the third band.

The variance measure (*VAR*) can be extended as *MVAR* (Multivariate Variance) to incorporate multiple bands of a remotely sensed image as follows. The individual independent variances VAR_1, VAR_2 and VAR_3 of R, G and B bands are found using Eq.(8) and combined into a single composite variance (MVAR) by applying the formula below.

$$MVAR = \frac{1}{3}\sum_{i=1}^{3}(VAR_i - \mu_3)^2 \text{ where } \mu = \frac{1}{3}\sum_{i=1}^{3} VAR_i \quad (10)$$

2.1.4 Global Description through Histogram:

The steps for global description of a multispectral image are given below.

i. Find local texture descriptor (*MFTM*) and local contrast variance descriptor (*MVAR*) for all pixels by using a sliding window neighbourhood (of size 3 × 3) that runs over the multispectral image from top left to bottom right.

ii. Compute the occurrence frequency of the ordered pair (*MFTM*, *MVAR*) into a 2D histogram.

2.2 KNN CLASSIFICATION ALGORITHM

The classification principle using KNN algorithm is listed below.

i. Extract global features of training samples and store them in the training database.

ii. Extract global feature of test sample.

iii. Find distances between the features of test sample and training samples stored in training database.

iv. Pick up '*k*' closest training samples.

v. Assign the class label of majority of K closest training samples as the class label of test sample.

2.3 DISTANCE MEASURES

In literature, distance measures have been applied to find dissimilarity between features in the form of one dimensional histogram. But in this paper, two dimensional histograms are used as global features and so the extended versions of distance measures are used.

2.3.1 Log Likelihood Distance:

In classification, the dissimilarity between a training sample and a test sample feature distribution is measured by a nonparametric statistical test called log likelihood [17] ratio.

$$G = 2\begin{bmatrix} \left[\sum_{s,m}\sum_{i=1}^{n}\sum_{j=1}^{k} f_{i,j}\log f_{i,j}\right] \\ -\left[\sum_{s,m}\left(\sum_{i=1}^{n}\sum_{j=1}^{k} f_{i,j}\right)\right]\log\left(\sum_{i=1}^{n}\sum_{j=1}^{k} f_{i,j}\right) \\ -\left[\sum_{i=1}^{n}\sum_{j=1}^{k}\left(\sum_{s,m} f_{i,j}\right)\right]\log\left(\sum_{s,m} f_{i,j}\right) \\ +\left[\left(\sum_{s,m}\sum_{i=1}^{n}\sum_{j=1}^{k} f_{i,j}\right)\log\left(\sum_{s,m}\sum_{i=1}^{n}\sum_{j=1}^{k} f_{i,j}\right)\right] \end{bmatrix} \quad (11)$$

where, s and m are the training and testing samples, n and k are the number of bins in two dimensions and $f_{i,j}$ is the frequency at bin pair (i, j). The computational complexity of this distance measure is medium.

2.3.2 Kullback Leibler Distance:

The Kullback Leibler distance (*KL*-distance) proposed in [15] is a natural distance function from a true probability distribution, p to a target probability distribution, q. For discrete probability distributions, $p = \{p_{11}, ..., p_{nk}\}$ and $q = \{q_{11}, ..., q_{nk}\}$, the *KL*-distance is defined to be,

$$KL(p.q) = \sum_{i=1}^{n}\sum_{j=1}^{k} p_{i,j}.\log_2\left(p_{i,j}/q_{i,j}\right) \quad (12)$$

where, $p_{i,j}$ and $q_{i,j}$ are the frequencies of training and test sample at bin pair (i, j). The computational complexity of this distance measure is medium.

2.3.3 Chi Squared Distance:

The chi squared (χ^2) distance can be derived as follows. Let 'X' be a discrete random variable with possible outcomes x_1, x_2, ……. x_m with probability of each outcome $P(X = x_i) = p_i$. Obtain 'n' independent observations. Bin the observations into 'm' groups, so that each group contains all observations having the same outcome x_i. Count the number of observations in each group to get n_1, n_2, …… n_k corresponding to the outcomes x_1, x_2,…... x_k so that $n = \sum n_i$. It is desired to find out how close the actual number of outcomes 'n_i' is to their expected values np_i. This distance is defined as,

$$\chi^2 = \sum_{i=1}^{m}\frac{(n_i - np_i)^2}{np_i} \quad (13)$$

The formula can be extended for comparison of two dimensional histograms as follows.

$$\chi^2 = \sum_{i=1}^{m}\sum_{j=1}^{k}\frac{(n_{i,j} - np_{i,j})^2}{np_{i,j}} \quad (14)$$

Here also $p_{i,j}$ refers to the frequency at bin pair (i, j). The computational complexity of this distance measure is medium.

2.3.4 Manhattan Distance:

The Manhattan distance function computes the distance to be traveled from one data point to the other if a grid like path is followed. The Manhattan distance between two items is the sum of the differences of their corresponding components. The formula for this distance between a point $X = (X_{1,1}, X_{1,2}, …… X_{n,k})$ and a point $Y = (Y_{1,1}, Y_{1,2}, …… Y_{n,k})$ is as follows.

$$d = \sum_{i=1}^{n} \sum_{j=1}^{k} \left| x_{i,j} - y_{i,j} \right| \quad (15)$$

where, n is the number of variables, and $X_{i,j}$ and $Y_{i,j}$ are the values of the $(i,j)^{th}$ variable, at points X and Y respectively. In this paper, the variables X and Y refer to the global features of training and testing sample containing frequencies at various pairs of bins respectively. The computational complexity of this distance measure is low.

2.3.5 Bhattacharyya Distance:

The Bhattacharyya distance (*BD*) [14] measures the similarity of two discrete probability distributions. It is normally used to measure the separability of classes in classification. For discrete probability distributions p and q over the same domain X, it is defined as:

$$BD(p,q) = -\ln\left(\sum_{x \in X} \sqrt{p(x)q(x)} \right) \quad (16)$$

The computational complexity of this distance measure is medium.

3. EXPERIMENTS, RESULTS AND DISCUSSION

This section describes the experiments, results and discussion on land cover classification of remotely sensed image using *MFTM / MVAR* texture model with log likelihood, Manhattan, Chi squared, Kullback Leibler and Bhattacharyya.

3.1 EXPERIMENTAL DATA

The remotely sensed image under study is a IRS P6, LISS-IV image [26] supplied by National Remote Sensing Centre (NRSC), Hyderabad, Government of India. The image has been taken in July 2007 and is of size 2959 × 2959. 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. It covers the area in and around Tirunelveli city located in the state of Tamil Nadu in India. It extends to the suburbs of Nanguneri village in the south, the outskirts of Palayamkottai in the north east, the suburbs of Alankulam village in the northwest and the suburbs of Ambasamudram in the south west. The river Thamirabarani runs across the diagonal region of the image. In the image, residential areas are either with closely packed buildings or with partially occupied buildings with shrubs and trees scattered then and there. Some tanks are present inside the city. Also in the south of Tirunelveli city leading to Nanguneri village several irrigation tanks and vegetation areas are present. In the North, bare soil is scattered in some places on the way to Sankarankoil. In the south west, on the way leading to Ambasamudram fertile paddy fields and vegetation are present on either sides of the perennial river. An updated geological map has been selected as a reference for ground truth study of the same area.

The experimental classes or training samples are the areas of interest extracted from source image in Fig.3 and are of size 16 × 16 as shown below in Table.1.

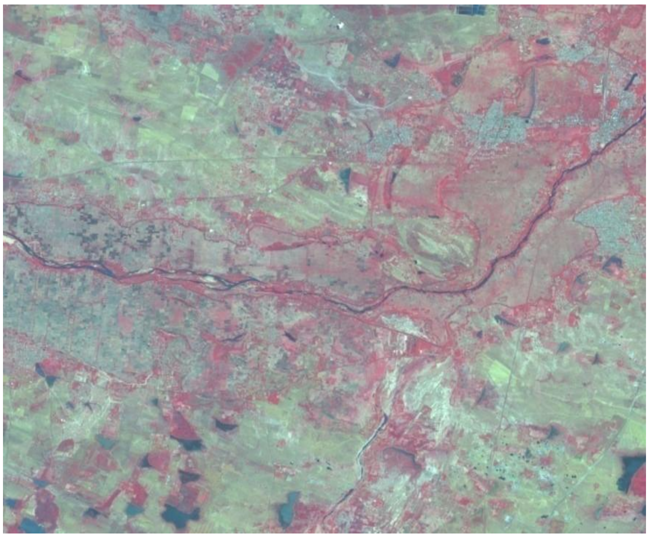


Fig.3. IRS P6, LISS-IV Remotely Sensed Image

Table.1. Training samples and their descriptions

Class No	Actual Class	Sample Used	Description
C1	Vegetation-1		Crops with tender sprouts
C2	Vegetation-2		Thick forest like vegetation
C3	Vegetation-3		Mature and ripe crops
C4	Settlement		Residential area
C5	Water		Water in rivers and ponds
C6	Soil		Barren land with sparsely and randomly scattered shrubs

In experiments for performing land cover classification of remotely sensed image, the size of training and testing samples were kept as small and close as possible to get better classification accuracy. So the window size of the testing sample was also fixed to 16 × 16. The threshold (n) and size of neighbourhood were fixed heuristically to 5 and 3 × 3 respectively. For ground truth verification, a set of stratified random samples comprising of 2400 pixels were taken from the remotely sensed image and used for building error matrix. Classification accuracy and kappa statistics were computed from the error matrix and used for performance evaluation.

3.2 PERFORMANCE METRICS

The overall classification accuracy (P_o), Kappa coefficient (K) and error matrix are the performance metrics for assessing the classified images in land cover classification. The error matrix can be built as follows. The size of error matrix is $c \times c$ where c is the number of classes. If a pixel that belongs to class i (where $1 \leq i \leq c$) is correctly classified, then a count is added in entry (i,i) of error matrix. If a pixel that belongs to class i is incorrectly classified to class j (where $1 \leq j \leq c$ and not $j \neq i$), then a count is added to the entry (i,j) of error matrix. The diagonal entries mark correct classifications while the upper and lower diagonal entries mark incorrect classifications. Then the overall accuracy (P_o) can be found as follows.

$$\text{Overall accuracy}\left(P_o\right)=\frac{\sum_{i=1}^{c} x_{ii}}{n} \tag{17}$$

where, n is the total number of observations and x_{ii} is the observation in row i and column i of error matrix.

The classification accuracy expected (P_e) and kappa coefficient are computed as in Eq.(16) and Eq.(17) respectively.

$$\text{Accuracy expected}\left(P_e\right)=\frac{\sum_{i=1}^{c} x_1 x_2}{n} \tag{18}$$

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

$$\text{Kappa Coefficient}(K)=\frac{P_o-P_e}{1-P_e} \tag{19}$$

3.3 EXPERIMENTAL SETUP

The overall classification procedure followed in all experiments is described as follows. In the training phase, training samples of size 16 × 16 were extracted from the remotely sensed image. In each training sample, for each 3 × 3 neighbourhood, the multivariate local texture feature (*MFTM*) and multivariate local contrast variance (*MVAR*) were found. The 2D histogram was formed for global description of a training sample. Then the 2D histograms of training samples were stored in the training database. In the testing phase, testing sample of size 16 × 16 was extracted from the remotely sensed image using a sliding window that runs from top left to bottom right in the remotely sensed image. The 2D histogram of test sample was found following the same procedure used for training samples. Then the 2D histogram of testing sample was given as input to the KNN classifier and the classifier returned the class label.

The performances of land cover classification experiments conducted using *MFTM* / *MVAR* descriptor with log likelihood, Kullback Leibler, Chi squared, Manhattan and Bhattacharyya distances are evaluated subsequently in this section. In KNN algorithm, the 'k' value was fixed to 3. The features in the form of two dimensional histograms are likely to have bins with zero entries in which case every empty bin is set to one (to avoid getting exception that arises when log 0 is found). The *MFTM* descriptor requires 46 bins while the *MVAR* values in Eq.(10) were quantized and binned in to 32 bins. So the size of the 2D histogram is (46 × 32).

3.3.1 Classification using MFTM/MVAR with Log Likelihood Distance:

The classified image is shown in Fig.4. The error matrix and accuracy total (P_o - Overall accuracy and K - Kappa coefficient) were found and the results are shown in Table.2 and Table.3 respectively.

The Settlement class is densely classified. The thin diagonal line tracing water is clearly seen. All texture classes are discriminated well and seen in the remotely sensed image. The pattern discrimination provided by log likelihood distance is so sharp that the boundaries separating classes are clearly traced.

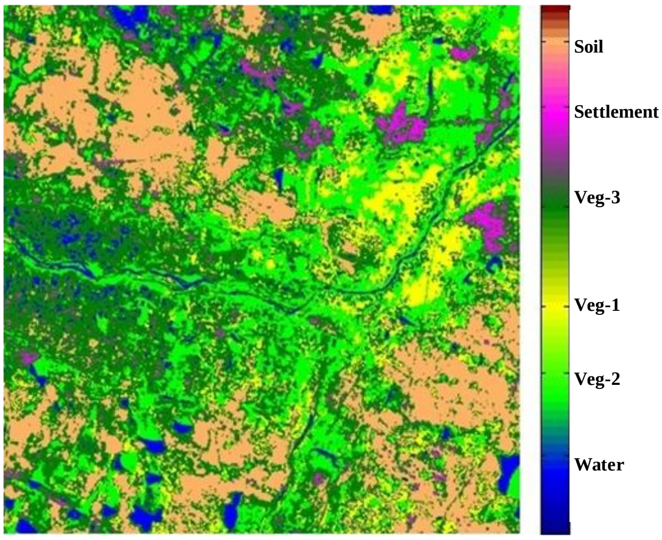


Fig.4. Classified image using log likelihood distance

Table.2. Error matrix - log likelihood distance

	BG	C1	C2	C3	C4	C5	C6	RoT
C1	0	98	1	6	0	0	0	105
C2	0	0	260	23	0	0	0	283
C3	1	1	4	607	9	0	29	651
C4	0	0	1	11	338	0	0	350
C5	1	0	0	4	0	249	0	254
C6	1	0	0	20	1	0	735	757
CoT	3	99	266	671	348	249	764	2400

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

Table.3. Accuracy total - log likelihood distance

Class No	RT	CT	NC	PA %	UA %
BG	0	3	0		
C1	105	99	98	98.99	93.3
C2	283	266	260	97.74	91.87
C3	651	671	607	90.46	93.24
C4	350	348	338	97.13	96.57
C5	254	249	249	100	98.03
C6	757	764	735	96.2	97.09
Total	2400	2400	2287		
Overall Accuracy =	95.29%	Overall Kappa =	0.9394		

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

3.3.2 Classification using MFTM/MVAR with KL Distance:

The classified image is shown in Fig.5. The error matrix and accuracy total (P_o and K) were found and the results are shown in Table.4 and Table.5 respectively.

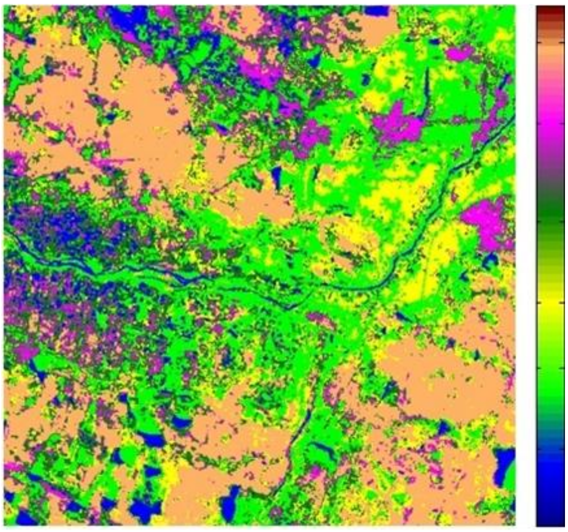


Fig.5. Classified image using KL distance

Table.4. Error matrix - KL distance

	BG	C1	C2	C3	C4	C5	C6	RoT
C1	0	93	2	69	0	0	1	165
C2	0	5	262	64	0	0	0	331
C3	0	0	1	341	1	0	2	345
C4	0	0	1	116	346	0	0	463
C5	1	1	0	24	0	249	0	275
C6	2	0	0	57	1	0	761	821
CoT	3	99	266	671	348	249	764	2400

Table.5. Accuracy total - KL distance

Class No	RT	CT	NC	PA %	UA %
BG	1	0	0		
C1	99	165	93	93.94	53.4
C2	266	331	262	98.5	79.15
C3	671	345	341	50.82	98.84
C4	348	463	346	99.43	74.73
C5	249	275	249	100	90.55
C6	764	821	761	99.61	92.69
Total	2400	2400	2293		
Overall Accuracy =	85.5%	**Overall Kappa=**	0.8171		

In the classified image, some pixels of Vegetation-3 class are misclassified to Settlement, Vegetation-1, Vegetation-2 and soil classes. To improve classification accuracy with KL distance further, a shape feature like moment can be included with the proposed descriptor. In such a case during classification using KNN, the distances between the shape features of test and training samples may be added with the distances between the texture features (obtained using the proposed descriptor *MFTM* / *MVAR*) of the same pair of samples.

3.3.3 Classification using MFTM/MVAR with Chi Squared Distance:

The classified image is shown in Fig.6. The error matrix and accuracy total (P_o and K) were found and the results are shown in Table.6 and Table.7 respectively.

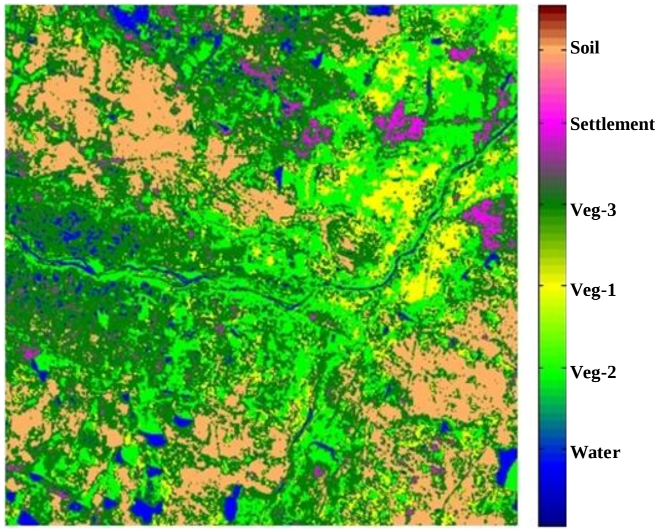


Fig.6. Classified image using Chi squared distance

Table.6. Error matrix - Chi squared distance

	BG	C1	C2	C3	C4	C5	C6	RoT
C1	0	90	1	1	0	0	0	92
C2	0	0	260	23	0	0	0	283
C3	1	9	4	639	21	1	84	759
C4	0	0	1	4	326	0	0	331
C5	1	0	0	4	0	248	0	253
C6	1	0	0	0	1	0	680	682
CoT	3	99	266	671	348	249	764	2400

Table.7. Accuracy total - Chi squared distance

Class No	RT	CT	NC	PA %	UA %
BG	3	0	0		
C1	99	92	90	90.91	97.8
C2	266	283	260	97.74	91.87
C3	671	759	639	95.23	84.19
C4	348	331	326	93.68	98.49
C5	249	253	248	99.6	98.02
C6	764	682	680	89.01	99.71
Total	2400	2400	2243		
Overall Accuracy =	93.46%	**Overall Kappa=**	0.9156		

The classification accuracy achieved is nearer to (±2) the classification accuracy reached with log likelihood distance. The

Chi squared distance is computationally simpler than log likelihood distance.

3.3.4 Classification using MFTM/MVAR with Manhattan Distance:

The classified image is shown in Fig.7. The error matrix and accuracy total (P_o and K) were found and the results are shown in Table.8 and Table.9 respectively.

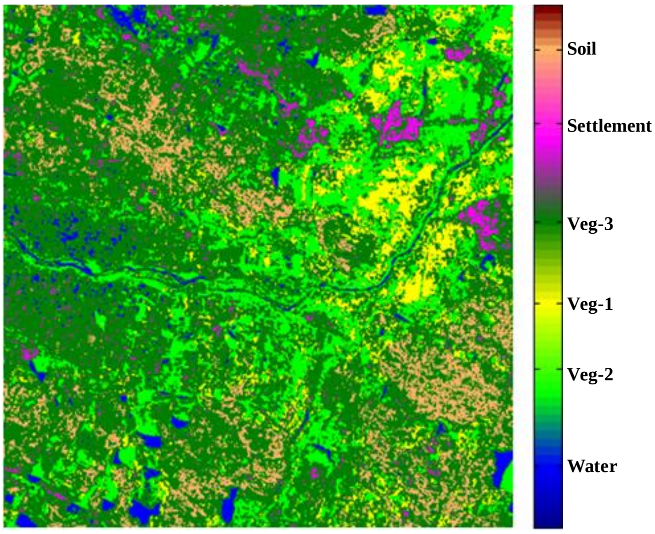


Fig.7. Classified image using Manhattan distance

Table.8. Error matrix - Manhattan distance

	BG	C1	C2	C3	C4	C5	C6	RoT
C1	0	79	2	1	0	0	0	82
C2	0	0	242	15	0	0	0	257
C3	2	20	21	649	57	15	435	1199
C4	0	0	1	5	291	0	0	297
C5	1	0	0	1	0	234	0	236
C6	0	0	0	0	0	0	329	329
CoT	3	99	266	671	348	249	764	2400

Table.9. Accuracy total - Manhattan distance

Class No	RT	CT	NC	PA (%)	UA (%)
Background	3	0	0		
C1	99	82	79	79.8	93.6
C2	266	257	242	90.98	94.16
C3	671	1199	649	96.72	54.13
C4	348	297	291	83.62	97.98
C5	249	236	234	93.98	99.15
C6	764	329	329	43.06	100
Total	2400	2400	1824		
Overall Accuracy =		76%	Overall Kappa=		0.6904

The classified image using Manhattan distance provides only satisfactory texture discrimination between various classes. The Vegetation-3 class dominates other classes in the classified image. The classification accuracy drops down because a major share of pixels belonging to soil class lying on either sides of the river basin is lost to Vegetation-3 class.

3.3.5 Classification using MFTM /MVAR with Bhattacharyya Distance:

The classified image is shown in Fig.8. The error matrix and accuracy total (P_o and K) were found and the results are shown in Table.10 and Table.11 respectively.

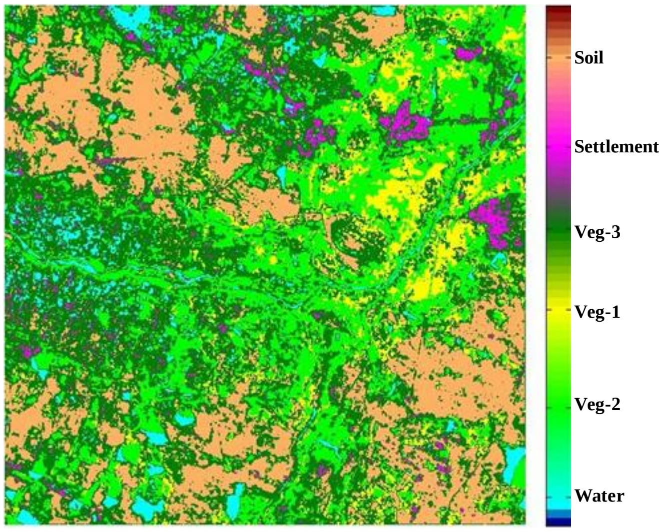


Fig.8. Classified image using Bhattacharyya distance

Table.10. Error Matrix- Bhattacharyya distance

	BG	C1	C2	C3	C4	C5	C6	RoT
C1	0	64	5	14	0	0	5	88
C2	0	0	261	30	0	0	0	291
C3	1	1	7	527	8	2	37	583
C4	0	0	1	24	367	0	5	397
C5	0	1	2	18	1	248	1	271
C6	1	0	0	0	3	0	766	770
CoT	2	66	276	613	379	250	814	2400

Table.11. Accuracy total- Bhattacharyya distance

Class No	RT	CT	NC	PA (%)	UA (%)
BG	0	2	0		
C1	88	66	64	96.97	72.73
C2	291	276	261	94.57	89.69
C3	583	613	527	85.97	90.39
C4	397	379	367	96.83	92.44
C5	271	250	248	99.2	91.51
C6	770	814	766	94.1	99.48
Total	2400	2400	2170		
Overall Accuracy =		93.04%	Overall Kappa=		0.9104

The Bhattacharyya distance performs equally well as chi squared distance (≈93%). All texture classes are seen in their places except along the left extreme side where some pixels of Vegetation-3 class are misclassified to Vegtation-2 and Settlement classes.

4. PERFORMANCE COMPARISON AND DISCUSSION

The classification accuracies obtained for *MFTM* / *MVAR* with log likelihood, Kullback Leibler, Chi squared, Manhattan and Bhattacharyya distances are 95.29%, 85.5%, 93.46%, 76% and 93.04% respectively. The kappa coefficients obtained for the above mentioned distance measures in the same order are 0.9394, 0.8171, 0.9156, 0.6904 and 0.9104 respectively. The graph in Fig.9 shows the classification accuracies and kappa coefficients of the classified images for comparison.

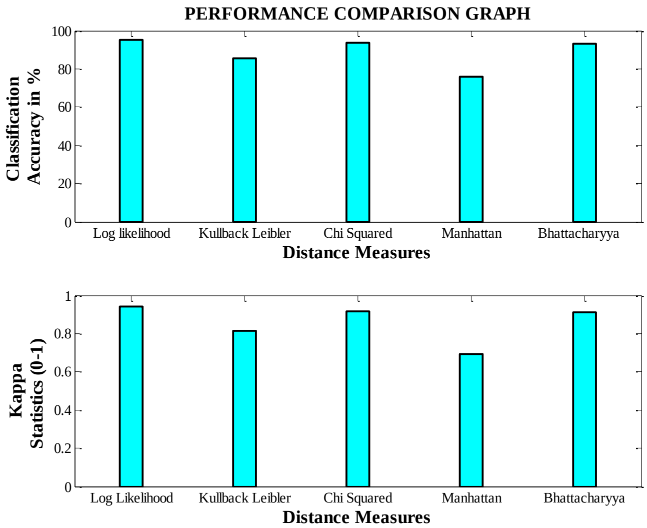


Fig.9. Performance Comparison Graph

In the experiments, the major difference in classification accuracy is caused by the abilities of distance measures to discriminate between Vegetation-3 and other classes. In the classified images obtained using distance measures other than log likelihood, some fraction of pixels of Vegetation-3 class got mixed up with other classes. Only log likelihood classified Vegetation-3 class matching the Vegetation-3 area of the reference map. So among the four distance measures evaluated, log likelihood distance is found better based on error matrix, classification accuracy and kappa statistics.

5. CONCLUSION

The effectiveness of a distance measure in giving high classification accuracy varies with the multivariate descriptor and the classification algorithm used. So texture classification of remotely sensed image has been performed with KNN and multivariate descriptor *MFTM* / *MVAR* using distance measures such as log likelihood, Kullback Leibler, Chi squared Manhattan and Bhattacharyya. All distance measures used in this paper are non parametric in nature and so they do not require the input to follow a definite probability distribution. From the experiments, it is inferred that the pattern discrimination provided by the distance measures is differential and log likelihood distance yields a high classification accuracy of 95.29% and kappa coefficient of 0.9394. Apart from these, the classification accuracies of results are sensitive to minor variations in training samples and window size implying that the selection of training samples and window size with precision is essential for getting good results. So each experiment has been carried out with various window sizes and precise training samples to yield optimal result.

The following extensions may be carried out for future research. A new distance measure can be proposed or an existing distance measure may be modified and a variant can be proposed. The variant can be proved to suit land cover classification application.

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