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MRF Based Enhancement on Classification of Hyperspectral Images Using CR Based Nearest Neighbor Classifier

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***Abstract**: Hyperspectral imaging is a collection of spectral details over an area using remote sensors where each image data represents dozens or hundreds of adjacent wavelength bands. Hyperspectral camera captures radiance or intensity for each pixel in the form of large number of contiguous spectral bands. This information can be used to uniquely identify spectrally similar information for accurate feature extraction and classification. Nearest neighbor classifier (NN) classifier is one of the classification methods that have been widely used in HSI analysis. The basic idea is to find a predefined number k of training samples in closest to the testing sample and assign the majority category label according to its k nearest training samples. Several extensions to k-NN are developed. In collaborative representation (CR) based nearest neighbor classifier the testing sample is represented as the linear combination of all the training samples. The problem with k-NN is that its performance highly depends on the selection of k and its features. The performance of the classification is improved by the proposed system, where Markov Random Field (MRF) is incorporated with collaborative representation of samples. Markov Random Field is a probabilistic model that can be used as post processing technique. Markov Random field gives a convenient way for modeling image pixels and correlated features by relabeling the neighboring pixels of misclassified pixels. The accuracy of classification is improved by the proposed system.*

***Keywords:** Classification, Hyperspectral imaging, Nearest neighbor classifier.*

1. INTRODUCTION

Hyperspectral imaging (HSI) is a recent breakthrough in the area of remote sensing. Human eye sees objects only in the visible light of electromagnetic spectrum where hyperspectral imaging acquires data across wide range of electromagnetic spectrum from ultraviolet to long infrared. Hyperspectral camera takes radiance or intensity for each pixel in the form of large number of contiguous spectral bands. Hyperspectral imaging provides deep information about the reflected image that contains object's spectral data [1].

Hyperspectral imaging is a stock of spectral details over an area using remote sensors where each image data represents dozens or hundreds of small, confined wavelength bands [2]. The continuous spectrum for an image cell can be prepared from these spectral bands. This color information helps to uniquely identify and distinguish similar objects.

The optical sensors transform the received energy into electric impulses. These impulses are translated into series of images and each image represents many spectral bands over a specified range. The spectral data is made into a form of hyperspectral image cube like a set of images put on top of one another. The data cube is a combination of three dimensions (x,y,λ) where x and y gives spatial dimensions and λ represents a set of wavelength. The spectral information can be compared with fields or reflectance spectra available in laboratory in order to uniquely identify and distinguish spectrally similar materials.

Object detection, material mapping and identification can be done using hyperspectral data. Reflectance statistics is used for classifying image pixels. Hyperspectral imaging helps to identify minerals for mining and oil industries. Hyperspectral image classification is defined as the process of producing maps of vegetation, road, roof and buildings from earth surface. There exist several techniques to perform classification where representative samples from land cover maps are used as training samples for the analysis.

Maximum Likelihood Classifier (MLC) [3] is the most frequently used classifier in remote sensing applications. It assumes a normally distributed multidimensional data space for each sample in the class. Decision making is done by Bayes theorem. Mean vector and covariance matrix is calculated from the normally distributed data space. The statistical probability for each class is computed using the characteristics and the undefined sample is assigned to one with highest probability value.

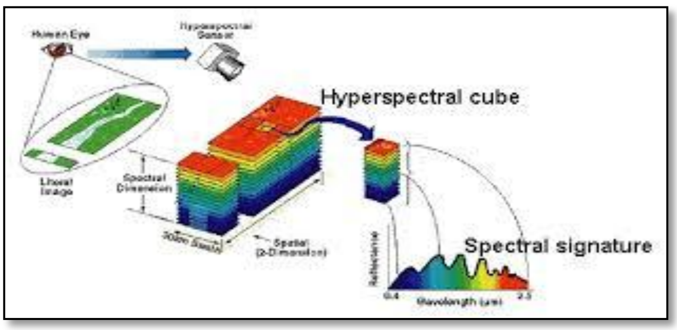

Figure 1: Hyperspectral Imaging

Nearest neighbor classifier [8] is the simplest classifier used in HSI analysis. It attempts to classify unknown pixels based on the neighboring pixels that are nearer to it. Based on the predefined number of samples, the majority category label is identified according to the closest training samples. k-NN

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classifier [5] selects k nearest training samples. The problem with this technique is that the performance highly depends on the selection of k and overlapping of classes reduces classification accuracy.

The local mean based nearest neighbor classifier (LMNN) is an extension of K-NN classifier. From the k nearest training samples in each class, the local mean vector is determined. Euclidean distance method is used for finding the similarity between data samples [7]. After calculating the mean vector per class, the class that minimizes the residual is identified as the class label of an unknown object.

In [4] Farid Melgani and Lorenzo Bruzzone introduced support vector machines (SVM) as the tool for hyperspectral image classification. Support vector machine exploits the concept of margin maximization instead of finding the statistical distribution of classes. SVM builds a classification model that assigns new sample into one class or other. The training samples of separate classes are divided by a clear gap that is as wide as possible. SVM determines a decision boundary that keeps the data points maximally away from each of the two categories. The margin of the classifier is calculated by the distance to the closest data points.

In [6] Wei Li, Qian Du,Fan Zhang, and Wei Hu introduced collaborative representation (CR)-based nearest neighbor classification (CRNN) technique. The test sample is considered in a collaborative form and weights for the representation is determined by l2-norm minimization-derived closed form solution.

By using l2-norm regularization method, the weight vector α is solved as follows:

$$\alpha = \arg\min_{\alpha} \| y - X_{\alpha} \|_2^2 + \lambda \, \|\Gamma_y \alpha\|_2^2 \quad (1)$$

where y denotes the testing sample, X is the set of training samples, Γ_y denotes biasing Tikhonov matrix and is λ the global regularization parameter. The minimization between the residual part and the regularization term is minimized by λ parameter. The regularization parameter, Γ_y is built in the form of

$$\mathbf{\Gamma_y} = \begin{bmatrix} \|\mathbf{y}-\mathbf{x}^{(1)}\|_2 & & 0 \\ & \ddots & \\ 0 & & \|\mathbf{y}-\mathbf{x}^{(n)}\|_2 \end{bmatrix}$$

where $x^{(1)}$, $x^{(2)}$,….$x^{(n)}$ denotes the columns of the training sample matrix X. The closed form solution for the weight vector can be solved as

$$\alpha = (X^T X + \lambda^2 \Gamma_y^T \Gamma_y)^{-1} X^T . y \qquad (2)$$

The k largest elements are selected from the calculated values. The number of weights associated with each class is determined from that and the testing samples label is found based on majority voting.

$$\text{class}(y) = \arg\max_{l=1,2,\ldots C} N_l(\alpha) \qquad (3)$$

where $N_l(\alpha)$ represents the no: of weights belonging to *l*th class.

The existing system performs classification based on the features of the available data sample. The problem of misclassification can occur in such situations.

The aim of this work is to improve the classification accuracy by incorporation any post processing technique along with classification. A collaborative representation (CR) is used to represent the testing sample in which a testing sample indicated as the combination of all training samples. The weights for the training samples are found by regularization methods. Markov Random Field is a probabilistic model that is used as post processing technique. The accuracy of classification is improved by incorporating Markov Random Field (MRF) along with collaborative representation. Markov random field gives a convenient way for modeling image pixels and correlated features by relabeling the neighboring pixels of misclassified pixels.

This paper is organized as follows. Session 2 describes the proposed work. Session 3 and 4 contains experimental setup and result analysis respectively. Session 4 gives conclusion and future work

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2. PROPOSED SYSTEM

The proposed system performs classification based on the unknown pixels nearest pixels instead of its features. The system increases the accuracy of classification by recalculating the classes of pixels using markov random field technique. A markov random field technique along with collaborative representation based nearest neighbor classification method is proposed

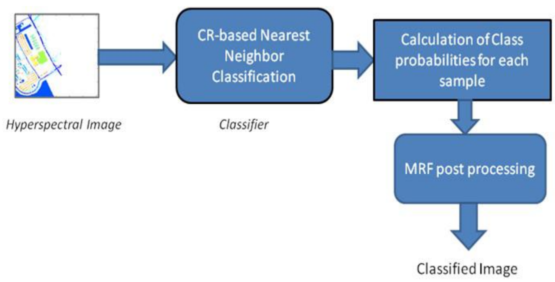

Figure 2: System Design

The system Architecture is shown in figure 2. The system mainly performs two tasks. For each data sample the class probabilities of each class is computed and markov random field post processing technique is applied.

2.1 Class Probability Calculation

The class probability refers to probability for a data sample belongs to a class. Instead of merely predicting the class label, the class probability measures the likeliness that a pixel belongs to a class. Collaborative representation based nearest neighbor (CRNN) classification is performed first. The weight vectors associated with each data sample is calculated as follows:

$$\alpha = (X^T X + \lambda^2 \Gamma_y^T \Gamma_y)^{-1} X^T . y \qquad (4)$$

Then the following steps are performed for each testing sample.

1. Determine the largest k weight vectors α for each test data point.
2. The total sum of weight vector is calculated.

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3. The sum of weight vector belongs to each class is calculated.
4. Divide the each class weight vector with total sum of weight vector to get the class probability.

The class probability is used as the input to markov random post processing technique.

2.2 Markov Random Field

Markov random field (MRF) modeling focuses on image classification problems. It can be treated as a tool for modeling an image data in order to get inferences about images. The basic idea of MRF is viewed as follows. The image is viewed as an assembly of nodes where nodes represent pixels. The value or color of pixel is indicated by assigning random variables to nodes. A joint probabilistic model is made over these random variables and pixels. The edge in the graph shows the statistical dependencies between random variables by explicitly grouping them [10].
MRF consists of an undirected graph G=(N, ε) where nodes indicates random variables. Consider Xs as the set of random variables associated with the set of nodes S. The conditional independence relationships is represented using edges, ε. Let A,B, and C denotes disjoint subsets of nodes. If there is no path exists from any node in A to any node in B that does not pass through a node of C then X_A is conditionally independent of X_B given X_C . If such a path does exist, the subsets are dependent. The neighbor set N_n of a node n is defined as the set of nodes that are connected to that node via edges in the graph,

$$N_n = \{ m \in N \mid (n,m) \in \varepsilon \} \qquad (5)$$

A node can be defined in terms of its neighboring nodes. A node n is independent of all other nodes if it has a neighbor set. The conditional probability of X_n can be written as follows:

$$P(X_n | P(XN - Xn) = P(X_n | X_{Nn}) \qquad (6)$$

Thus the Markov property for a pixel can be defined with respect to its neighboring pixels. The concept is illustrated by the following diagram:

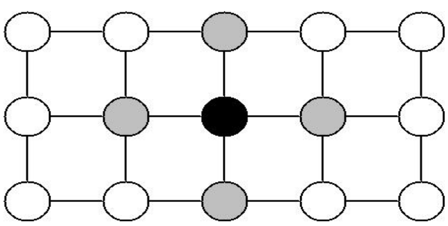

Figure 3: Neighborhood System**.**

In the figure the grey nodes are the neighbors of black node. According to markov property, the black node does not dependent on any other node.
In the MRF framework, the classification task is considered as an energy minimization problem on image pixels in a graph. The MRF energy function is computed as a sum of spectral and spatial energy terms. The chance of a pixel belonging to a specific class seems to be in the class that the neighboring pixels belonging to the same class.
The distribution over MRF can be expressed as the sum of potential function over the neighbor set of a pixel [9]. Spatially varying quantity such as intensity or disparity is needed to be estimated from noisy measurements in early vision problems. At most points, such quantities vary smoothly, and change dramatically at end points in objects (boundary). The quantities are to be piece wise smooth. The task is to find a labeling f that assigns a label to each pixel a, where f is consistent with the observed data and both piecewise smooth.

$$E(f) = E_{smooth}(f) + E_{data}(f) \qquad (7)$$

Here E_{smooth} relates to the interaction between neighboring pixels. E_{data} gives pixel wise information. For each pixel it measures the relation between the observed data and prior probabilistic model. The form of E_{data} as follows:

$$E_{data}(f) = \Sigma_{p \in P} D_p(f_p) \qquad (8)$$

where D_p is measured for each pixel.It calculates how appropriately a class label matches for a pixel in a graph. The smoothing term is expressed as follows:

$$^{E}\text{smooth} ^{=} \Sigma_{\{p,q\} \in N} V_{\{p,q\}} (f_p, f_q) \qquad (9)$$

where N shows the set of pairs of adjacent pixels. f_p,f_q represents the labels assigned for neighboring pixels.The MRF framework can be expressed as follows:

$$\omega' = \arg\min_{\omega}(-\Sigma_{i \in S} \log P(\omega_i/x_i) + \gamma \Sigma_{j \in Nxi} (1- \delta (\omega_i, \omega_j) \qquad (10)$$

where δ is called the Kronecker function,it function based on the following rule: $\delta (\omega_i, \omega_j)= 1$ for $\omega_i != \omega_j$, $\delta (\omega_i, \omega_j)= 0$ for $\omega_i = \omega_j$ .The neighboring pixels of x_i is expressed using $N(x_i)$,The resulting class labels after performing the MRF regularization is indicated by ω' , S is the set of all image pixels, and γ is a positive constant parameter that controls the spatial smoothing. The first term $P(\omega_i/x_i)$ characterizes the spectral information and it is derived from the collaborative k-NN. The second term is expressed by using a Potts model, which favors spatially adjacent pixels to belong to the same land cover class [11].
The Min-Cut problem is used to find the source to sink path with minimal cost. It is straightforward to show that the min-cut is a subset of the edges that reach capacity for the max-flow. Minimum energy is obtained by finding the min-cut in the graph.

3. EXPERIMENTAL EVALUATION

3.1 Implementation Details

The experimental data set of hyperspectral image was collected by the Reflective Optics System Imaging

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Spectrometer sensor. The image data set covers the city of Pavia, Italy. The German Aerospace Agency (DLR) collected the data set under the HySens project.

The spectral coverage of data ranges from 0.43 to 0.86 m and a spatial resolution is 1.3 m. The scene of university area has 103 spectral bands with a spatial coverage of 610×340 pixels. There are nine classes (i.e., Asphalt, Meadows, Gravel, Trees, Metal sheets, Bare soil, Bitumen, Bricks, and Shadow). In remote sensing the ground truth indicates the information captured over a location .The real features and objects on the ground can be referred to the image data. The ground truth map of pavia dataset set represents classifies image which shows nine different classes.

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Figure 4: Sample band of university of Pavia.

The following figure 5 shows the classes for respective samples:

Groundtruth classes for the Pavia University scene and their respective samples number

#	Class	Samples
1	Asphalt	6631
2	Meadows	18649
3	Gravel	2099
4	Trees	3064
5	Painted metal sheets	1345
6	Bare Soil	5029
7	Bitumen	1330
8	Self-Blocking Bricks	3682
9	Shadows	947

Figure 5: Groundtruth Classes for input dataset

The figure 5 shows nine classes and number of training samples collected from each class. The following figure 5 shows the Groundtruth image of pavia university dataset:

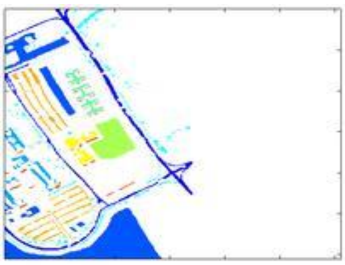

Figure 6: Groundtruth of pavia University dataset

4. TEST RESULTS

The hyperspectral image of pavia university contains 103 bands. The data set contains 207400 pixels where each sample has 103 features. The data set has nine classes. From each class 50 training samples were randomly selected. Thus there exist 450 training samples. The entire data set was used as the testing sample set. The weight vector for each testing data was calculated as per formula. For each testing data there would be 450 weight vectors. 10 largest weight vectors from the entire weight vectors were selected.

The label or class count related to each of largest weight vector was determined. The class that gives the maximum count is assigned as the class representation for the testing sample. The class probabilities for each data sample were calculated.

For each test data there were nine class probabilities. The dimension of input data set was 207400×9. The input data set of class probability was fed as input for post processing technique, markov random field. Markov random field recalculated the class for each test data and accuracy is measured. The following figure 7 shows the output image after performing CKNN and proposed system, MRF-CKNN.

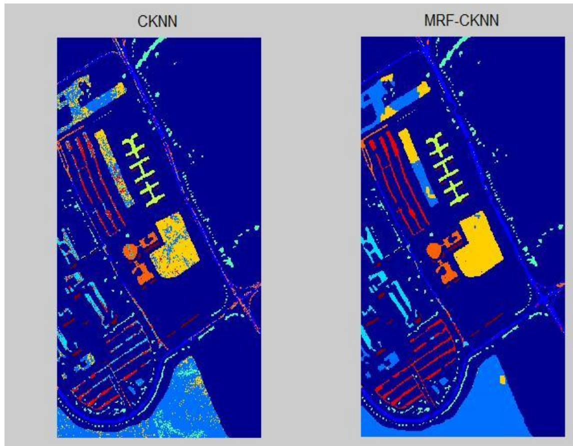

Figure 7: Output Image

Accuracy is measured in terms of number of correctly classified pixels to the total number of data samples. The CKNN method gave 78.40%. The proposed system gave 92.5% accuracy. The following graph shows the comparison of two methods based on accuracy.

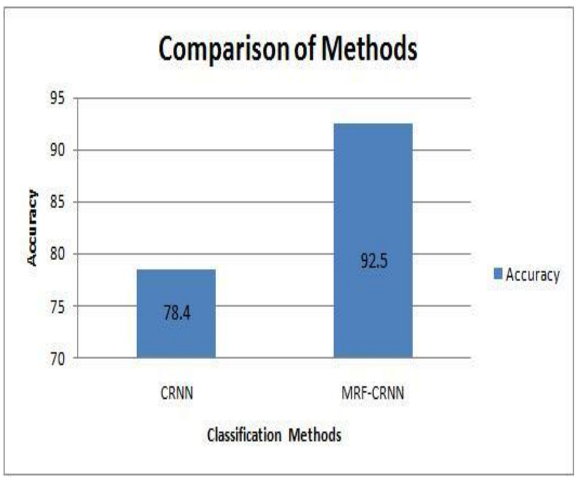

Figure 8: Comparison of Methods

5. CONCLUSIONS AND FUTURE WORK

Hyperspectral sensors provide ample information to accurately identify materials from a surface. Hyperspectral imaging has developed new opportunities in the field of image analysis and image classification. Spectral and spatial features are used for hyperspectral image classification. A major problem in hyperspectral image analysis is that spatial resolution gets worse when the spectral resolution increases.
Low spa-tial resolution causes issues in classification, since the pixels may contain more than one land cover classes. The collaborative representation based nearest neighbor classifier performs based on the features of closest training samples. The proposed system finds a simple and easy method to perform the classification of hyperspectral images. The performance of classification is improved by applying the post processing technique. The post processing technique, markov random field recalculates the class of an unknown pixel using nearest samples. Hence reduces the chances of misclassification. Accuracy of the classification is also improved by the proposed system.
The proposed system may perform badly in high dimensions (curse of dimensionality). Performance of classification can be further improved by reducing the time consumption. Dimensionality reduction algorithms such as principal component analysis can be done on the input data samples inorder to reduce the high dimension. There exist various methods for finding class probability. Class probability for a pixel can be computed by taking the count of weight vectors of the testing sample.

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