Satellite Image Classification Using Neural Networks

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Abstract— this paper is of classification of remote sensed Multispectral satellite images. Feature extraction techniques like mean, variance and standard deviation are used. Texture is the frequency of tonal changes on the image. The texture gives the 'rough' or 'smooth' appearance of the image. Higher resolution causes higher spectral variability within a class and lessens the statistical separability among different classes in a traditional pixel-based classification. Several methods of image classification exist and a number of fields apart from remote sensing like image analysis and pattern recognition make use of a significant concept.

Key Words: ISODATA, Multi-Layer Preceptron, Back propagation, Radial basis function, Self-organising Map

I. INTRODUCTION

An image is record of the features on the ground at the time of data collection. The image can be analyzed at different level of detail broad category (of least complexity for identification) could be water bodies and land cover. When multi-spectral data is obtained, the task is to identify the optimal three bands to generate the colour composite false colour composite (FCC) using green, red and NIR are the most preferred combination for visual interpretation. However, the analyst may initially experiment with different band combinations, ratios and suitable enhancement on sample imagery to assess which is best suitable for his analysis. IR colour images show vegetation in varying hues of red, since healthy vegetation reflects as to highest in the NIR (in FCC, NIR data is used as red). Texture is the frequency of tonal changes on the image. The texture gives the 'rough' or 'smooth' appearance of the image. Though both the green grass of pastureland and tree crowns has similar overall tone tree crowns will appear coarser or rougher compared to green grass. Texture is also dependent on the scale of imagery. A smooth texture may appear coarse at a larger scale. Size and shape are representation of the geometric arrangement of tone or colour of the pixels. Size of an object in the image depends on the scale. However, for the same scale, the relative size helps interpretation. The shapes of some objects are so distinctive as to make easy to distinguish, for example both highways and railways lines are linear, but always lines can be easily distinguished on the basis of its long stretches with slow curvature.

II. REMOTE SENSED IMAGES

Remote sensing image classification is one amongst the most significant application worlds for remote sensing [4]. The multispectral image is divided into spectrally homogeneous but non-contiguous segments using unsupervised classification [1]. Multispectral (MS) images in which we have observed images of the same zone through different spectral bands. The land cover types existing in the scanned zone constitute the sources to separate. Associating each source to a specific significant theme remains the real challenge in the source-separation method applied to satellite images. In fact, multispectral images consist of multiple channels, each channel containing data acquired from different bands within the frequency spectrum [2].

Merging spectral and textural classifications results in finer border delimitation and improves the overall classification accuracy of agricultural land-use as compared to textural classification alone. Higher resolution causes higher spectral variability within a class and lessens the statistical separability among different classes [5]–[6] in a traditional pixel-based classification. Therefore, classifying a pixel by using its own information alone is often regarded by the remote sensing experts as insufficient; hence they emphasize the use of the spatial context in which the pixel occurs, i.e., the information on the neighbouring pixels [5], [6]–[7]. Better land-use classification results, i.e., assignation of the *type* of crop (the land-use class) to each parcel, have been reported while using texture features than while classifying without them [8], [9]. Morphological features such as shape, area, length, width, perimeter, area/perimeter ,also features like mean, variance and standard deviation, spectral and textural features are then used collectively to classify the regions Because of their simplicity and easy handling, the k- means clustering [10] and the Nearest Neighbour (NN) classifier [11] are used for unsupervised and supervised classifications, respectively The MS image originally has four bands, including near infrared (NIR), red (R), green (G), and blue (B) bands, acquired at the spatial resolution of 2.8 m/pixel. But the blue band provides with very faint reflectance variability and is not very discriminative for vegetation covers. Hence, only the first three spectral bands (NIR, R, and G) were pan-sharpened to enhance their spatial resolution. **S**ource separation is relatively a new area of data analysis. It consists of recovering a set of signals of which only instantaneous linear mixtures are observed. Source separation has received significant attention due to its suitability to recover sources when no information is available about the mixture. This problem is known as blind source separation Regarding remote sensing, this technique is recently adapted to obtain more accurate representation of the soil to provide a land-cover classification [12]–[14]. In fact, for many geosciences applications, we have to convert remotely sensed images to ground-cover maps. To solve this classification problem, mixing scales and linearity of distinct materials have been investigated by several researchers. Over the last decades, numerous approaches to extract ground-cover information from remotely sensed images have been developed. The usual method to produce ground-cover maps is pixel based classification that consists in allocating each pixel to only one of some preselected classes, which supposes good domain knowledge. This constitutes a serious limit for this method. The source separation can be obtained by optimizing a scalar measure of some distributional property of the output, called contrast function. It can be based on entropy, mutual information, higher order statistics, etc. [15]. The application of the source-separation method on multispectral images transforms them into independent images, providing more efficient representation of the information given by each image.

III. SPECTRAL ANALYSIS

TABLE I

Band	Wave length	Used For
Blue	450-515..520nm	Atmospheric and deep water imaging and reach within 150feet(50m) deep in clear water
Green	515..520-590..600nm	Imaging of vegetation and deep water structure, up to 90 feet (30m) in clear water.
Red	600..630-680..690	Imaging of manmade object, in water up to 30 feet(9m)deep, soil and vegetation
Near Infrared	750-900nm	Primarily for imaging of vegetation
Mid-Infrared	1550-1750nm	Imaging vegetation, soil moisture content, and some forest fires.
Mid-Infrared	2080-2350nm	Imaging soil moisture, geological features, silicates, clays and fires.
Thermal Infrared	10400-12500nm	Emitted radiation instead of reflected, for imaging of geological structures, thermal differences in water currents, fires and for night studies

Basically, image segmentation divides an image into spatially contiguous, disjunctive, and spectrally homogenous regions [17] as shown in Table I. In this work, we perform what is usually referred to as global segmentation, using an algorithm of unsupervised spectral classification, also known as clustering. But this may lead to spectrally homogenous clusters that are not necessarily spatially contiguous and may consequently result in the so called “salt and pepper effect” [18]. To alleviate this effect, we pre-processed the multispectral imagery with a Gaussian low-pass filter having the dimensions of 8 X 8 pixels. Smaller the value of the standard deviation σ more is the “salt and pepper effect” in the segmentation result.

IV. CLASSIFICATION

Remote sensing image classification can be viewed as a joint venture of both image processing and classification techniques. Generally, image classification, in the field of remote sensing is the process of assigning pixels or the basic units of an image to classes. It is likely to assemble groups of identical pixels found in remotely sensed data into classes that match the informational categories of user interest by comparing pixels to one another and to those of known identity. Several methods of image classification exist and a number of fields apart from remote sensing like image analysis and pattern recognition make use of a significant concept, classification. In some cases, the classification itself may form the entity of the analysis and serve as the ultimate product. In other cases, the classification can serve only as an intermediate step in more intricate analyses, such as land degradation studies, process studies, landscape modelling, coastal zone management, resource management and other environment monitoring applications. As a result, image classification has emerged as a significant tool for investigating digital images.

The purpose of classification and mapping of vegetation over large spatial scales remotely sensed data are generally used. A better understanding of data is necessary for further advances. The analyst must select a classification method that will best accomplish a specific task. At present it is not possible to state which classifier is best for all situation as the characteristics of each image and the circumstances for each study vary so greatly.

In this, the pixel values in the R, G and B bands were extracted. Clusters were defined accordingly. The cluster corresponding to minimum distance was assigned the respective pixel. Shown below is the original image and its classified output. Different landcover types in an image can be discriminated using some image classification algorithms using spectral features, i.e. the brightness and "colour" information contained in each pixel. The classification procedures can be "supervised" or "unsupervised". In supervised classification, the spectral features of some areas of known landcover types are extracted from the image. These areas are known as the "training areas". Every pixel in the whole image is then classified as belonging to one of the classes depending on how close its spectral features are to the spectral features of the training areas. In unsupervised classification, the computer program automatically groups the pixels in the image into separate clusters, depending on their spectral features. Each cluster will then be assigned a landcover type by the analyst. Each class of landcover is referred to as a "theme" and the product of classification is known as a "thematic map". An edge can be defined as a discontinuity in grey-level, colour, texture, etc.

IV.A. Supervised Classification

The remote sensing literature presents with a number of supervised methods that have been developed to tackle the multispectral data classification problem. The statistical method employed for the earlier studies of land-cover classification is the maximum likelihood classifier. In recent times, various studies have applied artificial intelligence techniques as substitutes to remotely-sensed image classification applications. In addition, diverse ensemble classification method has been proposed to significantly improve classification accuracy. The quality of a supervised classification [19] depends on the quality of the training sites. All the supervised classifications usually have a sequence of operations that must be followed.

1. Defining of the Training Sites.
2. Extraction of Signatures.
3. Classification of the Image.

The training sites are done with digitized features. Usually two or three training sites are selected. The more training site is selected, the better results can be gained. This procedure assures both the accuracy of classification and the true interpretation of the results. After the training site areas are digitized then the statistical characterizations of the information are created. These are called signatures. Finally the classification methods are applied.[16]

A multispectral image covers enormous areas of land cover and is inherently difficult to process on this entire multispectral image. A ground truth image (reference image) is generated by field study campaign. Random sampling is carried out to select the pixels for training and testing the classifiers

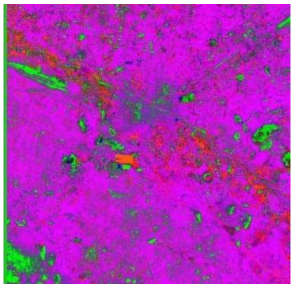

Fig. 1 IRS-1D imagery

IV.A.1Artificial Neural Network (ANN) Classifier

A multi-layered feed-forward ANN [14] is used to perform a non-linear classification. The classified image is shown in Fig.2. This model consists of one input layer, at least one hidden layer and one output layer and uses standard back propagation for supervised learning. Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output. The error is back propagated through the network and weight adjustment is made using a recursive method. The classified image is shown in Fig. 5

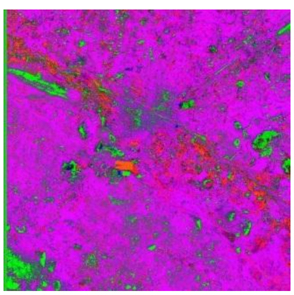

Fig.2 Neural Network Classification

IV.B. Unsupervised Classification

Edge information from a gradient edge detector is integrated with a segmentation algorithm. The multispectral edge detector uses all available multispectral information by adding the magnitudes and directions of edges derived from edge detection in single bands. The addition is weighted by edge direction, to remove "noise" and to enhance the major direction. The resulting edge from the edge detection algorithm is combined with a segmentation method based on a simple ISODATA algorithm, where the initial centroids are decided by the distances to the edges from the edge detection step [3].The algorithm for delineating agricultural field boundaries is divided into three parts. The first part is a multispectral edge detection where the main boundaries are found and correctly located. The second step is an unsupervised classification using an ISODATA algorithm [20] integrated with the results from the edge detection step and the third step is to merge regions from the over-segmentation in step two. Fig. 8 shows the flow diagram of the main processing steps of the field delineation algorithm

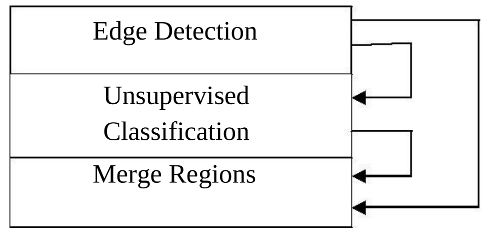

Fig 3. Flowchart of the segmentation algorithm for agricultural fields.

IV.B.1 Merging of Regions

The unsupervised classification procedure produces too many regions in the initial clustering step. By calculating the mean and covariance matrix (1) for pixels of neighbouring regions, regions having a high generalized likelihood ratio test quantity will be merged. Neighbouring regions are assumed to be as two multivariate normal distributions with mean vectors $\mu_1$and μ_2 and covariance matrices Σ_1 and Σ_2 in an image with number of bands

$$\hat{\Sigma} = \frac{\sum_{i=1}^{b}(x_i x_i^T) - n\mu\mu^T}{n} \qquad (1)$$

The MLP (Multi-Layer Preceptron) has been the most popular neural network model. Compared with the MLP, a RBF neural network only has a single hidden layer, which results in exponentially decreasing computation complexity. Radial basis function (RBF) neural networks have been applied in many research fields since it was proposed, especially in pattern recognition, function approximation and time series predication. An efficient technique for improving the classification accuracy of multi-spectral satellite image data is essential for obtaining reliable materials which can supply enough information for both environment protection and natural resource development.

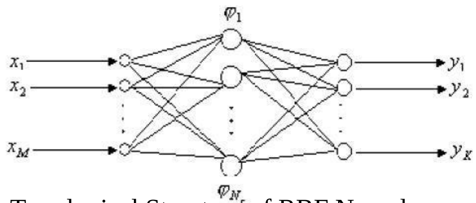

Fig 4. Topological Structure of RBF Neural Networks

In the RBF neural networks, radial basis functions are embedded into a two layer feed-forward neural network. The network has a set of inputs and a set of outputs. Between the inputs and outputs there is a layer of processing units referred to as hidden units. Each hidden unit is implemented with a radial basis function.

In the RBF neural networks, the nodes of the hidden layer generate a local response of input prompting through the radial basis functions, and the output layer of RBF neural networks realize the linear weighted combination of the output of the hidden basis functions. The spectral method is used in the unsupervised learning part of the **NRBF** neural networks. The classified image is shown in Fig. 6

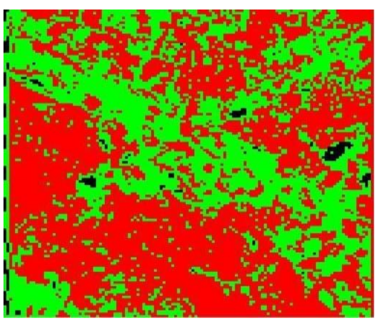

Fig 5. Back propagation Classification

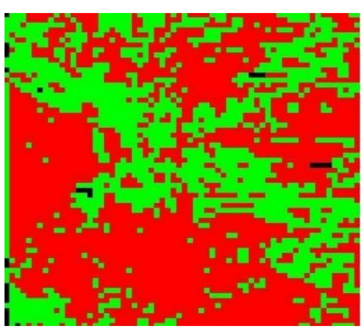

Fig 6. Radial Basis Function Classification

A Self-Organizing Map (SOM) or self-organizing feature map (SOFM) is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretized representation of the input space of the training samples, called a map. Self-organizing maps are different from other artificial neural networks in the sense that they use a neighborhood function to preserve the topological properties of the input space. This makes SOMs useful for visualizing low-dimensional views of high-dimensional data.

This technique is used for a wide variety of purposes, including speech recognition, industrial process control, image analysis, data mining, anomaly detection, DNA sequencing, data visualization, climate downscaling, demographics, and more.

V. CONCLUSIONS

In this paper we have compared the performance of various classifiers. Realization by a spectral and spatial separation exploiting the spectral correlation between contiguous bands and spatial correlation between neighboring pixels. The spectral separation allows the representation of multispectral data according to independent axes, which offers more discrimination and increases the reliability of the analysis and the interpretation of these images. The information from all spectral bands both for finding edges and for clustering pixels into homogeneous areas. The method is completely automatic and supervised. The segmentation and the classification procedures can be carried in parallel; the proposed method is faster than the region- based or object-based methods in which the classification process must follow the prior segmentation process. Naturally, the classification accuracy using the NN classifier depends on the size of the processed blocks. This accurate but simple classifier shows the importance of considering the data set - classifier relationship for successful image classification. The misclassification can be improved using ensemble classification.

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