Supervised and Unsupervised Neural Network for Classification of Satellite Images

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ABSTRACT

This paper is of classification of remote sensed Multispectral satellite images using supervised and unsupervised neural networks. Feature extraction techniques like mean, variance and standard deviation are used. 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. The combination of multiple classifiers is done for designing high performance pattern classification systems.

Keywords

Multi-Layer Preceptron, Back propagation, Radial basis function, Self-organising Map,Voting Algorithm

1. INTRODUCTION

The multispectral image is divided into spectrally homogeneous but non-contiguous segments using unsupervised classification [1]. In multispectral images 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 multispectral images as compared to textural classification alone. Higher resolution causes higher spectral variability within a class and lessens the statistical separability among different classes [3–5] 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 [3], [4–5]. 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 [6] and the Nearest Neighbour (NN) classifier [7] are used for unsupervised and supervised classifications, respectively.

The Multispectral image originally has four bands, including near infrared (NIR), red (R), green (G), and blue (B) bands. 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 This technique is recently adapted to obtain more accurate representation of the soil to provide a land-cover classification [8–10]. 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 [11]. 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.

2. CLASSIFICATION

Remote sensing image classification can be viewed as a joint venture of both image processing and classification techniques. 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 modeling, 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. Fig 1 is the Original Landsat image on which the processing is done.

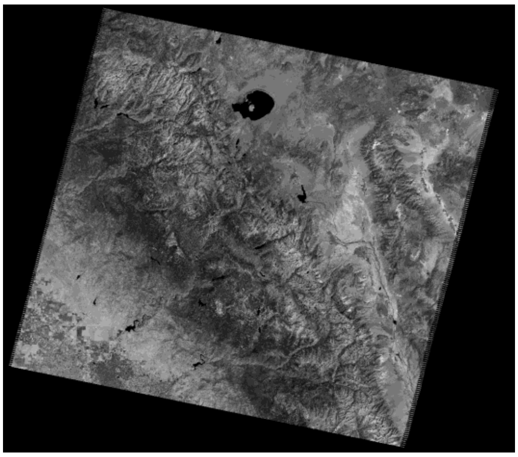

Fig 1: Owens_valley-band5 (Landsat Image) [14]

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.

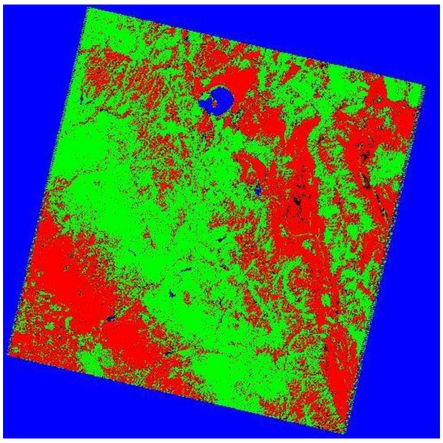

Fig 2: RGB equivalent of the original Image

In this, the pixel values in the R, G and B bands were extracted. Fig 2 is the RGB equivalent of the original Landsat image. 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.

3. SUPERVISED CLASSIFICATION

In recent times, various studies have applied artificial intelligence techniques as substitutes to remotely-sensed image classification applications. An ensemble classification method has been proposed to significantly improve classification accuracy. The quality of a supervised classification [13] 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 [12]. A multispectral image covers enormous areas of land cover and is inherently difficult to process on this entire multispectral image. Random sampling is carried out to select the pixels for training and testing the classifiers.

A multi-layered feed-forward ANN [10] is used to perform a non-linear classification. The classified image is shown in Fig. 3,4 and 6. 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. 3

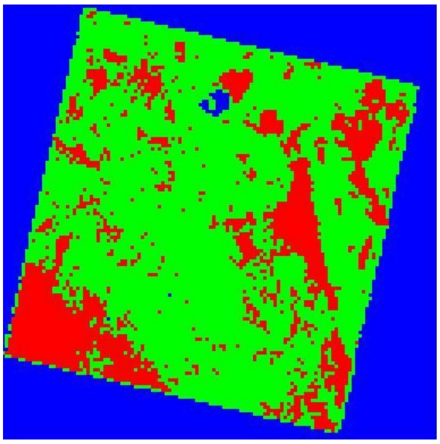

Fig 3: Classified Image using Back propagation Algorithm

The MLP (Multi-Layer Preceptron) has been the most popular neural network model. Compared with the MLP, a Radial basis function (RBF) neural network only has a single hidden layer, which results in exponentially decreasing computation complexity. RBF neural networks have been applied in many research fields 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.

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. The classified image is shown in Fig. 4. 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 Normalized-RBF neural networks.

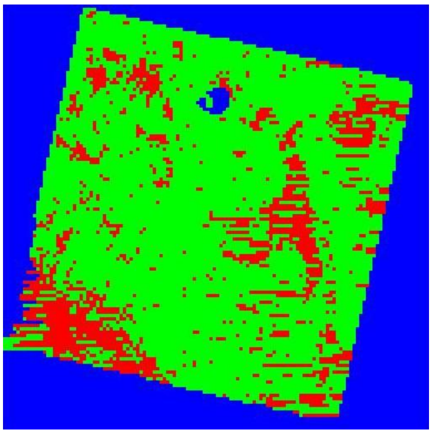

Fig 4: Classified Image using Radial Basis Function

4. UNSUPERVISED CLASSIFICATION

The 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 unsupervised classification procedure produces too many regions in the initial clustering step. By calculating the mean and covariance matrix using (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 μ_1 and μ_2 and covariance matrices Σ_1 and Σ_2 in an image with number of bands

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

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. The classified image is shown in Fig. 5.

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.

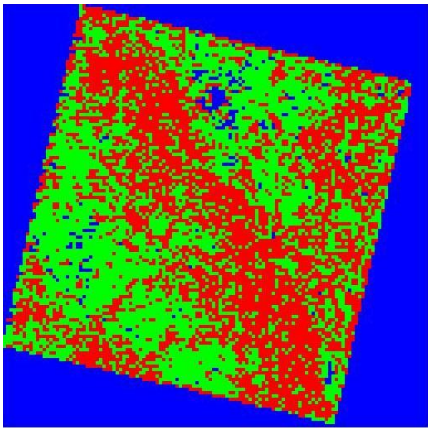

Fig 5: Classified Image using Self Organizing Map

5. VOTING ALGORITHM

This is one of the method of ensembling the classifier. In this algorithm, the combination of multiple classifiers is done for designing high performance pattern classification systems. We consider ensemble formed by these three different classifiers i.e back propagation, radial basis function and Self organizing map. Here these three classifiers are combined in the vote as a base classifier and to the voted classifier as the combined classifier. A simple method to combine results provided by different classifiers is to interpret each classification result as a vote for various data classes [15]. The data classes that receives a number of votes higher than the prefixed threshold is taken as the final classification. The classified image using voting algorithm is shown in Fig. 6

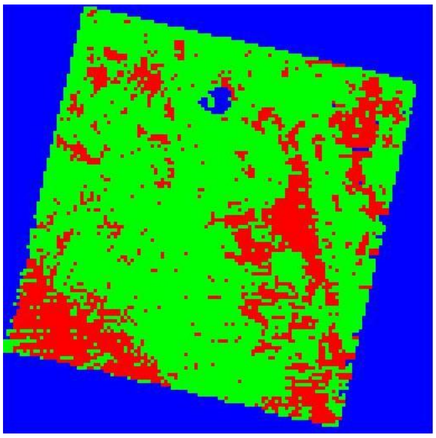

Fig 6: Classified Image using Voting Algorithm

6. 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 method is automatic and supervised for backpropagation and radial basis function and unsupervised for Self-organizing map. The combination of multiple classifiers is done for designing high performance pattern classification systems which combine results provided by different classifiers is to interpret each classification result as a vote for various data classes. The misclassification is also improved by this technique. 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.

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