Generalized Cooccurrence Matrix to Classify IRS-1D Images using Neural Network

E. Hosseini Aria [a], M.R.Saradjian [a], J. Amini [a], and C. Lucas [b]

[a] Remote Sensing Division, Surveying and Geomatics Engineering Department,
Faculty of Engineering, University of Tehran, Tehran, Iran
aria@engineer.com , sarajian@ut.ac.ir, jamini@ut.ac.ir

[b] Electrical and Computer Engineering Department,
Faculty of Engineering, University of Tehran, Tehran, Iran

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ABSTRACT:

This paper presents multispectral texture analysis for classification based on a generalized cooccurrence matrix. Statistical and texture features have been obtained from the first order probability distribution and generalized cooccurrence matrix. The features along with the gray value of the selected pixels are fed into the neural network. Frist, Self Organizing Map (SOM) that is an unsupervised network, has been used for segmentation of IRS-1D images. Then a generalized cooccurrence matrix and first order probability distribution have been extracted from each kind of segments. Texture features have been obtained from generalized cooccurrence matrix. The matrices describe relevant "texture" properties of classes. Next, feature vectors are generated from the extracted features. Then the image is classified by Multilayer Perceptron (MLP) network which has been trained separately using the selected pixels. The method used in this paper has been tested on the IRS-1D satellite image of Iran. The Experimental result is compared to the Maximum Likelihood Classification (MLC) result and it has been shown the MLP method is more accurate than MLC method and also is more sensitive to training sites.

1. INTRODUCTION

Artificial neural networks can be seen as highly parallel dynamical systems consisting of multiple simple units that can perform transformation by means of their state response to their input information. How the transformation is carried out depends on the Neural Network (NN) model and its way of learning the transformation. Neural network learns by example. In a typical scenario, a neural network is presented iteratively with a set of sample, known as the training set, from which the network can learn the values of its internal parameters.

During the last few years the number of reported applications about the use of neural network in remote sensing, have been steadily increasing. The majority of applications have used the multilayer perceptron neural network trained with back-propagation algorithm although applications employing the self-organizing feature maps have also been reported.

MLP networks are general-purpose, flexible, and nonlinear models consisting of a number of units organized into multiple layers. The complexity of the MLP networks can be changed by varying the number of layers and the number of units in each layer. Given enough hidden units and enough data, it has been shown that MLPs can approximate virtually any function to any desired accuracy. MLPs are valuable tools in problems when one has little or no knowledge about the form of the relationship between input vectors and their corresponding outputs.

In order to approach higher classification accuracies it is necessary to consider texture information and neighborhood information around each pixel. A cooccurrence matrix gives some texture information. Augusteijn *et al.* (Augusteijn ,1995) compared the performance of several texture measures for classifying land cover classes in satellite images. One of these texture measures was cooccurrence matrices. Their experiments showed that neural networks can give excellent results with texture features.

Since the feature extracting is time consuming process for the whole image, the image segmentation has been made first. Image segmentation is the process of division of the image into regions with similar attributes (Pratt, 2001). The self-organizing map has been used successfully for image segmentation (Ohta, 1980). The algorithms have been implemented on the IRS-1D images from which three spectral bands have been selected and fused with the PAN band to create an image with 5.8 m spatial resolution.

2. FEATURE EXTRACTION

Remotely sensed data and the land cover/land use classification of urban areas set their own requirement for feature extraction. Features should be easily computed, robust, insensitive to various distortions and variations in the images, and they should support the discrimination of the land cover/land use classes.

In this paper the following two basic feature groups are used:

-Statistical features showing the intensities and intensity variations of pixels.

-Texture features based on gray level cooccurrence matrix.

2.1 Statistical features

The most basic of all image features is some measure of image amplitude in terms of luminance, spectral value, or other units. One of the simple ways to extract statistical features in an image is to use the first-order probability distribution of the amplitude of the quantized image. They are generally easy to compute and largely heuristic. The first order histogram estimate of $P(b)$ is simply

$$P(b) = \frac{N(b)}{M} \qquad (1)$$

where b is a gray level in an image,

M represents the total number of pixels in a neighborhood window of specified size centered around the pixel, and

N(b) is the number of pixels of gray value b in the window where $0 \le b \le L-1$.

Now the following measures have been extracted by using first order probability distribution (Pratt, 2001).

Mean:

$$S_M = \bar{b} = \sum_{b=0}^{L-1} bP(b) \qquad (2)$$

Standard deviation:

$$S_D = \sigma_b = \left[\sum_{b=0}^{L-1}(b-\bar{b})^2 P(b)\right]^{1/2} \qquad (3)$$

Skew-ness:

$$S_S = \frac{1}{\sigma_b^3}\sum_{b=0}^{L-1}(b-\bar{b})^3 P(b) \qquad (4)$$

Kurtosis:

$$S_K = \frac{1}{\sigma_b^4}\sum_{b=0}^{L-1}(b-\bar{b})^4 P(b) - 3 \qquad (5)$$

Energy:

$$S_N = \sum_{b=0}^{L-1}[P(b)]^2 \qquad (6)$$

Entropy:

$$S_E = -\sum_{b=0}^{L-1} P(b)\log_2\{P(b)\} \qquad (7)$$

The first two features are the mean and standard deviation of pixel intensities within the image window.

In order to get information on the shape of the distribution of intensity values within window, the skewness and kurtosis are determined. The skewness, characterizes the degree of asymmetry of the intensity distribution around the mean intensity. If skewness is negative, the data spread out more to the left of the mean than to the right. If skewness is positive, the data are spread out more to the right.

The kurtosis measures the relative peakness or flatness of the intensity distribution relative to the normal distribution. The kurtosis of the normal distribution is 3. Distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3. Lower outlier-prone distributions have kurtosis less than 3.

The energy and entropy are also determined. The energy is useful to examine the power content (repeated transitions) in a certain frequency band. Entropy is a common concept in many fields, mainly in signal processing (Coifman, 1992).

2.2 Texture features

Many land cover/land use classes in urban areas can be distinguished from each other via their shape or structure characteristics. Therefore, it is important to extract features that are able to describe relevant "texture" properties of classes. In other researches, different kinds of texture feature such as multi channel filtering feature, fractal based feature and cooccurrence features (Ohanian, 1992) have been proposed. In the proposed algorithm for classification, the cooccurrence features are selected as the basic texture feature detectors due to their good performance in many pattern recognition applications including remote sensing

It should be noted that when computing cooccurrence features using all or relatively high number of possible pixel intensity values, the derived texture information will be easily blurred by noise in the image (Ohanian, 1992). Hence, it is preferable to transform the original intensity values into a small number of possible levels either via a scalar or vector quantization method. For the cooccurrence feature extraction in this study, the original image pixel intensities which have been in 256 different discrete values were transformed into the set {0,1,…,31} by histogram transformation (Gonzales, 1993).

A gray level cooccurrence matrix is defined as a sample of the joint probability density of the gray levels of two pixels separated by a given displacement. In Cartesian coordinates the displacement of the cooccurrence can be chosen as a vector $(\Delta x, \Delta y)$. The gray level cooccurrence matrix N is defined as

$$N(i,j)=\{\#pair\ (i,j) | image(x,y)=i \text{ and } image(x+\Delta x, y+\Delta y)=j\}$$

where i,j are gray levels.

The cooccurrence matrices extracted from each band have been combined to avoid data redundancy. This generalized matrix calculates average of the gray level cooccurrence matrices. We used $\Delta x=0$, $\Delta y=2$ to generate the generalized cooccurrence matrix in this research.

Second-order histogram features are based on the gray level cooccurrence matrix. This histogram estimate of the second-order distribution is

$$P(a,b) \cong \frac{N(a,b)}{M} \qquad (8)$$

where M is the total number of pixels in the measurement window and $N(a,b)$ is obtained from cooccurrence matrix (Ohta, 1980). If the pixel pairs within an image are highly correlated, the entries in $P(a,b)$ will be clustered along the diagonal of the array. The measures listed below have been proposed as measures that specifies the energy spread about the diagonal of $P(a,b)$.

Autocorrelation:

$$S_A = \sum_{a=0}^{L-1}\sum_{b=0}^{L-1} abP(a,b) \qquad (9)$$

Covariance:

$$S_C = \sum_{a=0}^{L-1}\sum_{b=0}^{L-1}(a-\bar{a})(b-\bar{b})P(a,b) \qquad (10)$$

where

$$\bar{a} = \sum_{a=0}^{L-1}\sum_{b=0}^{L-1} aP(a,b) \qquad (11)$$

$$\bar{b} = \sum_{a=0}^{L-1}\sum_{b=0}^{L-1} bP(a,b) \qquad (12)$$

Inertia:

$$S_I = \sum_{a=0}^{L-1}\sum_{b=0}^{L-1}(a-b)^2 P(a,b) \qquad (13)$$

Absolute value:

$$S_V = \sum_{a=0}^{L-1}\sum_{b=0}^{L-1} |a-b| \ P(a,b) \qquad (14)$$

Inverse difference:

$$S_F = \sum_{a=0}^{L-1}\sum_{b=0}^{L-1} \frac{P(a,b)}{1+(a-b)^2} \qquad (15)$$

Energy:

$$S_G = \sum_{a=0}^{L-1}\sum_{b=0}^{L-1} [P(a,b)]^2 \qquad (16)$$

Entropy:

$$S_T = -\sum_{a=0}^{L-1}\sum_{b=0}^{L-1} P(a,b) \log_2 \{P(a,b)\} \qquad (17)$$

The measures mentioned above to specify the texture have been applied in this study. The utilization of the second-order measures for texture analysis is considered in section 5.

3. SEGMENTATION

Segmentation of an image entails the division or separation of an image into regions of similar attribute. The most basic attribute for segmentation is image luminance amplitude for a monochrome image and color components for a color image. Image edges and texture are also useful attribute for segmentation.

Artificial neural networks are being increasingly employed in various fields such as signal processing, pattern recognition, medicine and so on. An approach to compress color image data using a SOM is proposed, with the intention to generate a code table for color quantization for data transformation (Godfery, 1992).

The present work deals with the color subset and describes an attempt to segment color image based on a self organizing neural network, which is able to recognize main components (chromaticities) presente t seltic delta rules. This algorithm operates in the batch mode and is invoked using the train.

5. EXPERIMENT AND RESULTS

In this section, the classification process stages that have been explained in previous sections are implemented. Figure 2 shows the flowchart of the algorithm stages. To implement the algorithm, IRS-1D satellite image from a region in the north of Iran has been used. Bands 2, 3, and 4 of LISS-III image have been selected and fused with the PAN band to construct an image with 5.8 m spatial resolution.

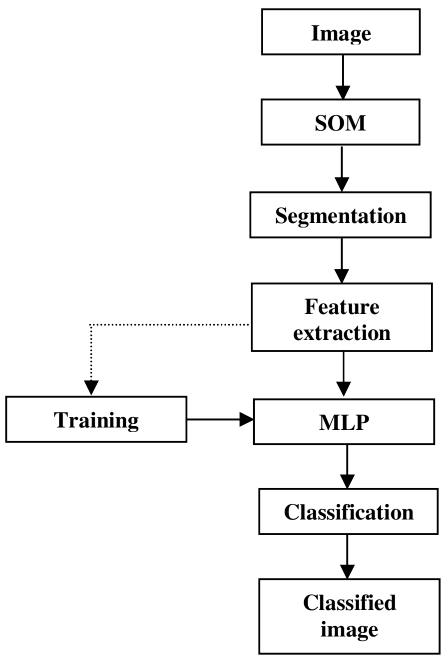


Figure 2. Flowchart of land cover classification using ANN.

The proposed segmentation utilizes a self-organizing map to detect the main features present in the image. The features are represented by their chromaticity value, which expresses colors hue and saturation, avoiding the luminance component.

The network is composed of an orthogonal grid of cluster units, each associated to three orthogonal weights for the chromaticity data. The initial values for weights are set to random values before the learning phase. The produced segmented image includes 40 different segments. The image constructed from segmentation process is illustrated in figure 4(b). One indicator pixel from each kind of segments has been selected.

Then, the features have been extracted from image with a window centered on the indicator pixel. The sizes of the windows are variable. The statistical features were computed from a window with 3×3, 5×5, 7×7 pixels size. In order to extract texture features, the size of the feature extraction window has been variable as 9×9, 11×11 and 13×13 pixels.

Then, multilayer perceptron network has been designed and trained using training data. The training diagram for network is shown in figure 3.

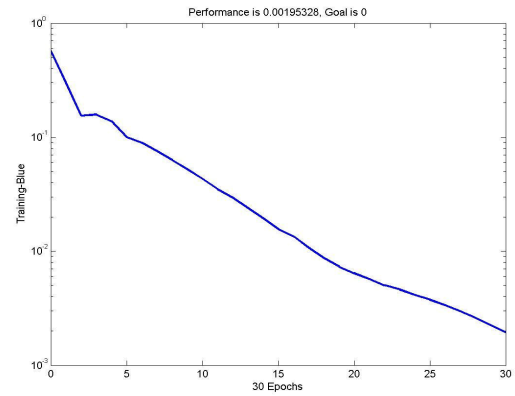


Figure 3. Training diagram for MLC network

Finally, the extracted statistical and texture features with the intensity of the central pixel of each window are arranged in a vector and fed to the MLP network. The MLP identifies the class number of each segment. The classified image has been shown in the figure 4(c).

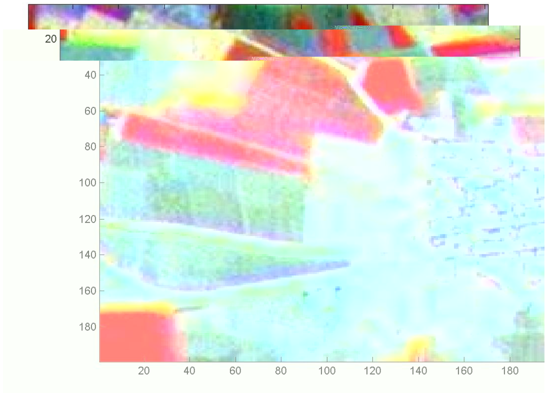
The MLP experimental results have been compared to Maximum Likelihood Classification (MLC) method that is one of the conventional classification methods based on statistics. The maximum likelihood decision rule is based on the probability that a pixel belongs to a particular class. The basic equation assumes that these probabilities are equal for all classes, and that the input bands have normal distributions. Figure 4(d) shows a classified image obtained using MLC.

In order to assess the accuracy of each classification method, 200 random points were considered for each classification maps. Then, they have been compared with the reference map to compute the overall classification accuracy. The obtained overall accuracies using MLC and BPNN methods are 78.50% and 86.19% respectively. Hence, from a global accuracy assessment view, the NN method employed in this research has shown a significant improvement in classification of IRS images compared to MLC method.

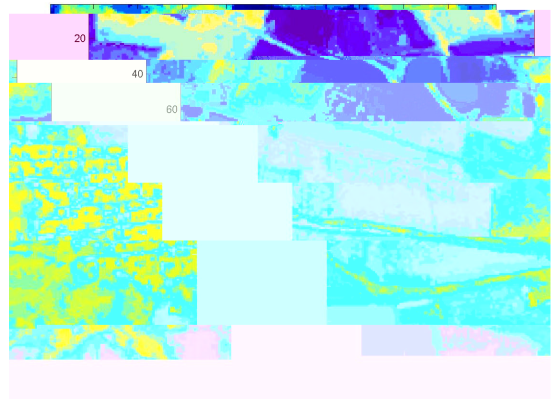
6. CONCLUSIONS

In comparison of the neural network classification method implemented in this study to the maximum likelihood method on an IRS-1D image, it has been concluded that the neural network method is more accurate than MLC method. As mentioned previously, the overall accuracy in the neural network method has shown great improvement. Also, the neural network method is more sensitive to training sites than MLC. The sensitivity may be regarded as an improvement to the algorithm.

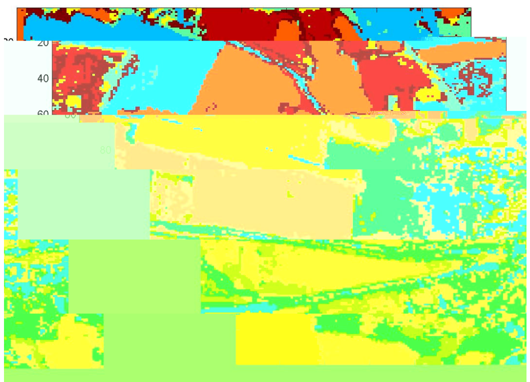
By applying the segmentation prior to the classification, the classified image contains more improved edges compared to the MLC method. As another improvement, the MLP method does not classify those unnecessary pixels that is not trained for and avoid misclassifications. However, the MLC method particularly when using this image has classified all pixels even for those that has not been trained for.



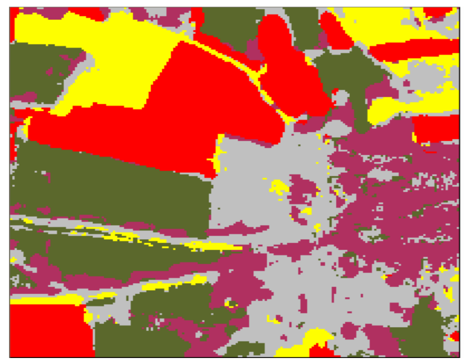
(a) Original image



(b) Segmented image



(c) Classified image using MLP



(d) Classified Image using MLC

Figure 4: The classification process, (a) The original image of IRS-1D satellite, (b) Segmented image using SOM method, (c) Classified image using MLP method, and (d) Classified image using MLC method.

Using segmemation in this study, efficiency of the classification process has also been improved. This is due to the segmemation made before feature extraction to avoide time consuming process of redundant data processing in feature extraction stage. Also, with regards of efficiency of the process, Resilient back propagation that is generally much faster than the standard steepest descent algorithm has been applied. It also has the appropriate property that requires only a modest increase in memory requirements. This enables us to store the updated values for each weight and bias which is equivalent to storage of the gradient.

7. REFRENCES

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