Endmember Extraction by a Self-Organizing Neural Network on Hyperspectral Images

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Abstract

The present work exploits the possibility of using a Self-Organizing Neural Network to obtain the endmembers (class prototypes) on hyperspectral images. The Self-Organizing neural network has the advantage that obtains by competitive procedures this endmembers on hyperspectral images.

We propose a neural network for processing the spectral information for each pixel. The neural model consists of a Self-Organizing Neural Network. This net has an input neuron for each image channel. The output neuron number is related with the endmember number. Different distances and learning functions are used to obtain a better endmember extraction.

The result discussion also includes the neighborhood function and the influence of noise in the endmember quality.

1 Introduction

The use of hyperspectral imaging sensor data to study the Earth's surface is based on the capability of such sensors to provide high-resolution spectra (hyperspectral signature), one per pixels basis, along with the image data. This capability can be used to determine Earth's surface constituents from the spectral information provided by the sensor.

Highly successful results have been obtained following this approach, particularly in the field of geology were exposed lithographies have been mapped based on specific mineral spectral reflectance signatures [1].

In most of hyperspectral signal processing applications it is necessary to determine the components in a composite pixel spectrum obtained from a given mixture of elements. This problem is known as Hyperspectral Unmixing.

The Hyperspectral Unmixing addresses the problem of performing an inventory of landscape objects or components that are patchy or significantly smaller than the size of the pixel in remotely sensed imagery.

Formally, the problem may be considered as follows: Each pixel spectrum is modeled as a linear combination of the hyperspectral signatures of a finite number of ground components (endmembers).

If the hyperspectral signatures of the endmembers are known in advance, it is possible to invert the model to determine the unknown composition of the target using the hyperspectral signature of the corresponding pixel.

The main intention of this paper is to explore the possibility of using a Neural Networks Methodology to obtain a reliable, robust and efficient solution to the Hyperspectral endmember identification problem based on the performance of neural networks.

Many applications have been presented in this field. Adams et al. [2] studied this problem in the context of Surface Mineralogy Prospection, and Lawton [3] proposed conventional digital algorithms for its solution. Standard spectroscopic methods are generally time-consuming when used on millions of spectra, and they are hindered by remote sensing complications (atmosphere, sensor artifacts, mixtures).

Ideal hyperspectral imagery analysis techniques would treat the spatial and spectral patterns in the data simultaneously [4].

A method based on the Optical Neural Network was presented by Barnard and Cassasent [5]. To find the composition of a mixture knowing its spectrum and the spectrum of the possible components, a quadratic cost function was minimized to find the optimal.

The possibility of using the Multiple Regression Theory, granting an optimal solution in terms of uniqueness, has been developed by Díaz et al. [6]. This approach explore also the possibilities for improving the robustness of the proposed method, that consists of the use of the Pseudo-Inverse Matrix, supported by a Linear Associative Memory, built using the Pyle's algorithm.

The general solution method is based on the Hopfield Recurrent Neural Network (HRNN). It is a flexible, efficient and robust approach to solve the problem has been proposed by us (Pérez et al. [7],[8],[9]). The Gradient Method for minimizing errors is used to assure the convergence of the algorithm. The use of this model is fully justified since the composition spectrum formation is essentially a linear process.

The snag about these solutions is that they include constrains that is necessary to make a previous selections of all the possible endmembers.

Some hyperspectral unmixing methods include one endmember selection tool:

P.P.I.

The method proposed by Kruse [10] consists of some analysis steps:

(a) Minimum Noise Fraction (M.N.F). This transformation was used to determine the inherent dimensionality of the hyperspectral data, similarly to the Principal Component transformations but maximizing the signal–noise ratio.
(b) Pixel Purity Index (P.P.I.). The P.P.I. is a means of finding the most spectrally pure pixels, which typically correspond to spectrally unique materials (endmembers). The P.P.I. is computed by repeatedly projecting n-dimensional MNF scatterplots onto a random unit vector. The extreme pixel in each projection is marked and a counter (D.N.) indicates the total number of times they have been marked. In a P.P.I. image the pixel value is the D.N. counter, pixels with higher D.N. values are the most spectrally pure (endmember).

M.E.S.T.

The manual endmember selection tool (MEST) is a computer display for interactively deriving spectral endmembers from multispectral and hyperspectral datasets.

The first step in the selection process is determination of the number of mixture components via a principal component analysis (PCA). If the PCA finds that most of the variance in the data is accounted for by N orthogonal directions (referred to as eigenvectors), then the number of endmembers is N+1 and the MEST displays the spectral data mean corrected and projected into N-dimensional space determined by the first N eigenvectors. This space is referred to as the mixing space [11].

The MEST provides the user with a means to explore the mixing space in search of N+1 spectra that are acceptable as the spectral signatures of ground components and that contain the spectral data in the simplex they span in the mixing space

S.O.M

Our studies develop a self-organizing neural network for the analysis of hyperspectral images.

The self-organizing neural network (S.O.M.) is based on the competitive learning to form topologic maps. This way, after the learning process is finished, when presenting a spectrum to the network only the neurons closely related to the given spectrum are activated.

This kind of network was introduced by T. Kohonen [12] and has been successfully applied in many different fields: analysis and comprehension of images, artificial vision, optical characters reading, analysis and recognition of voice, musical and acoustic studies and telecommunications.

Within the spectroscopic analysis S.O.M. has been successfully applied in protein classification tasks, microbiology and infrared spectroscopy.

This work consists on studying the topologic maps formed by the self-organizing neural network to classify the pixels of a hyperspectral image in order to find the endmembers in a composite pixel (hyperspectral unmixing).

Most of the neural processing algorithms are computationally intensive and involve many iterative calculations. The formerly mentioned algorithms use basically matrix operations such as internal product and external product. In this way the MatLab© software pack offers an appropriate environment to carry out experiments with neural network, due to its facility for the matrix and vectorial notation and its graphic possibilities. This allows the fast implementation of neural computational models and the chance to test them.

2 Proposed Neural Network

A neuron is an information-processing unit that is fundamental to the operation of a neural network. We may describe three basic elements of the neuron model:

(c) A set of synapses or connecting links, characterized by its weight. Specifically, a signal x_j at the input of synapse j connected to neuron k is multiplied by the synaptic weight w_{kj}.
(d) An adder for summing the input signals, weighted by the respective synapses of the neuron.
(e) An activation function for limiting the amplitude of the output of a neuron.

A layered neural network is a set of neurons organized in the form of layers. In the simplest form of a layered network, we just have an input layer of source nodes that projects onto an output layer of neurons. The input layer has N units, and can be considered as a n-dimensional vector. The output layer has M units and can be also seen as a vector. Each unit owns N weights associated to the connections which come from the former layer, so the weight set is a matrix (W_{MxN}). Fortunately, neural networks can often be described with matrixes. So the chosen tool to design the neural network must have vectorial and matrix facilities. Our proposed network architecture is described in Figure 1 (Aguilar [13]).

We consider the one-dimensional lattice of M neurons, which contains two different types of connections. There are feedforward connections from the N input layer neurons, and those that are internal to the network by virtue of self-feedback and lateral feedback. These two types of local connections serve two different purposes. The weighted sum of the input signals at each neuron is designed to perform feature detection. Hence each neuron produces a selective response to a particular set of input signals. The feedback connections, on the other hand, produce excitatory or inhibitory effects, depending on the distance from the neuron [12].

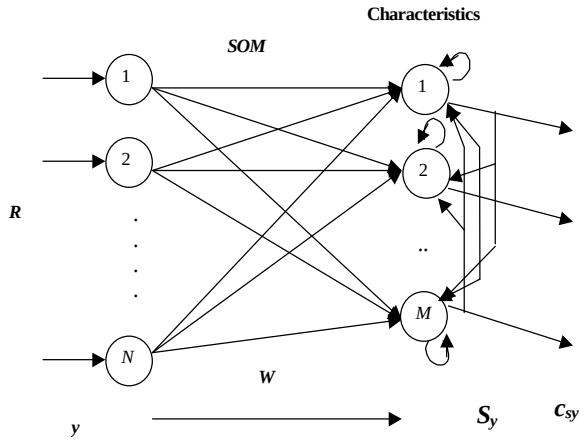

Figure 1. Proposed architecture.

There are five basic steps involved in the application of the training algorithm. These five steps are repeated until the map formation is completed. The algorithm is summarized as follows:

(a) *Initialization*. Choose random values for the initial weight vectors $\boldsymbol{w_i}$ **(0)** (i = 1,2,...,M). It is desirable to keep the magnitude of the weights small.

(b) *Sampling*. Choose an input pattern x(n) belonging to the learning patterns or references (**R**). The selection can be randomly.

(c) *Similarity Matching*. Find the best-matching (winning) neuron **i*** at the time t, using the minimum-distance criterion, as eqn (1) shows:

$$i^*[x(n)] = \min_j \; dist\{x(n), w_j(t)\} \quad j = 1,2,\cdots,M \tag{1}$$

(d) *Learning*. Adjust the synaptic weight vectors of all neurons, using the update formula (2), where η(t) is the learning-rate parameter, and γ(t,i,i*[x(n)]) is the neighborhood function centered around the winning neuron.

$$w_i(t+1) = w_i(t) + \eta(t)\gamma\left(t, i, i^*[x(n)]\right)\left(x(n) - w_i(t)\right) \tag{2}$$

(e) *Continuation*. Continue from step 2 until no noticeable changes in the weight space are observed, or the maximum time is been achieved.

3 Training

The layer of the neural network must be trained with hyperspectral signatures from the pixels of the image. This learning process is very important in the neural network performance (noise cancellation and endmember spectra extraction).

The number of endmember abundance to obtain determines the number of neurons on the output layer of the SOM.

In order to select a set of initial values (step 1), related with the image, the weights initially associated with each endmember neurons contain the hyperspectral signatures of some carefully selected pixels on the image (according with the spatial distribution).

One of the problems associated with the training phase is the use of mixture pixels as training patterns. Assuming that two endmembers have been correctly learnt, they can be added in a mixture spectrum, the problem is related with the possibility of learning new endmembers with this composition. One classical SOM will learn this composition as new endmembers. To avoid this possibility, in order to assure that the stored endmembers are as independent as possible, we propose to introduce a modification in the competitive learning that detect co-linearities between the trained and the learnt patterns.

In this sense, we use as distance a function of the angle between the input pattern ***x(n)*** and the weight vector of the neuron *j*, it can be calculated as:

$$dist\{x(n), w_j(t)\} = \arccos\left(\frac{x(n).w_j(t)}{\|x(n)\|\|w_j(t)\|}\right) \tag{3}$$

This distance has the advantage that is invariant to the scale changes on the vectors, and it depends only of the directions in the N-dimensional vector.

Table 1 shows the results obtained from testing the below algorithm with both Euclidean and angular type distance.

To test the performance of the SOM, we use 3 endmembers, labeled as $\boldsymbol{e_1}$, $\boldsymbol{e_2}$ and $\boldsymbol{e_3}$, (vectors) and another vectors obtained by re-scaling these endmembers with different factors (2* $\boldsymbol{e_1}$, 2* $\boldsymbol{e_2}$, 2* $\boldsymbol{e_3}$, 3* $\boldsymbol{e_1}$, 3* $\boldsymbol{e_2}$ and 3* $\boldsymbol{e_3}$).

We can see that the classification is different in both cases; when we use the Euclidean distance, the network obtains more number of endmembers (in the Table 1, all the classes are present) because it makes a bad classification for vectors whose unique difference is a scale factor. This problem is solved when we use the angle that forms only a class for every endmember (scaled or not).

(Endmember Number : Endmember coefficient)

	$\boldsymbol{e_1}$	$\boldsymbol{E_2}$	$\boldsymbol{e_3}$	2 $\boldsymbol{e_1}$	2 $\boldsymbol{e_2}$	2 $\boldsymbol{e_3}$	3 $\boldsymbol{e_1}$	3 $\boldsymbol{e_2}$	3 $\boldsymbol{e_3}$
Euc.	1	4	7	2	5	6	9	3	8
Angle	1	2	3	1	2	3	1	2	3

Table 1. Influence of distances in classification.

Endmember extraction from mixtured hyperspectral signatures

Most of the hyperspectral signatures of the image pixels correspond to mixtures of some basic endmembers, this situation can be show on figure 2, where the values of band 1 are shown graphically versus the band 2 values.

The figure clearly shows the presence of two endmembers , the first one with higher values of band 2 and the other with higher values of band 1. The intermediate values of band 1 and band 2 (in the center of the figure) are obtained by mixtures of the related endmembers.

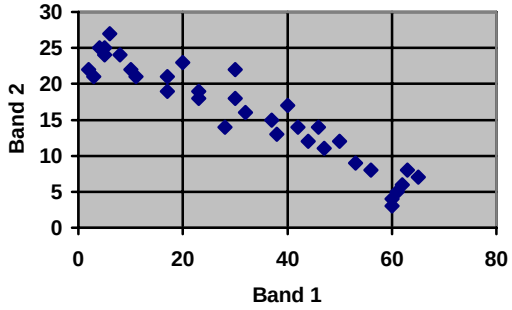

Figure 2. Band 1 against Band 2.

In order to avoid that the network learns this mixtures as new enmembers, we propose the use of a neighborhood function that eliminates the corresponding neurons.
After the training set ($x_1, x_2,...,x_N$) has been presented to the SOM, we have information about the projection of their spectral signatures x_i on the predicted endmember spectral signatures e_j ($1 \le j \le M$).
When one spectral signature x_i vector is used, we obtain the winner neuron i^* with eqn 3; and the output neurons offer the projection $x_i.e_i$ of this vectors on each endmember e_i.
Taking the weights vector of the winning neuron w_{i^*} as SOM input, each neuron j computes $w_j.w_{i^*}$.
To evaluate these projections, we compute the mean of then for all the neurons:

$$\overline{P}_{i^*} = \frac{1}{M}\sum_{j=1}^{M} w_j w_{i^*} \qquad (4)$$

And the standard deviation of this projections:

$$\sigma_{i^*} = \frac{1}{M}\sum_{j=1}^{M}\left(P_{ji^*} = \overline{P}_{i^*}\right)^2 \qquad (5)$$

In this sense, we propose a neighborhood selection criteria based on the standard deviation σ_{i^*} of these projections, described in equation 6, where μ is one adjustable parameter related with the discrimination criterium and f is a non decreasing function.

$$\gamma\left(t, j, i^*[x(n)]\right) = \begin{cases} 0 & \text{if } 1-\left(w_j.w_{i^*}\right) > \mu\sigma_{i^*} \\ \sigma_{i^*} f\left(w_j.w_{i^*}\right) & \text{in other case} \end{cases} \qquad (6)$$

Typically, a winner neuron (i^*) with high σ_{i^*} values corresponds to a mixture signature and its weights must be updated; on the other hand, a winner neuron (i^*) with lower σ_{i^*} values corresponds to an endmember signature and its weights must be preserved.
This criteria is equivalent to use a topology were the most similar neurons are nearest than those whose weight vector is more different, according with the angular distance described above.
For this purpose, we use the learning function described in eqn 2, according to the special neighborhood function described in eqn 6.

4 Results

To test the performance of the SOM, we use 2 endmembers, labeled as p_1 and p_2 , and another vectors obtained by mixtures of both endmembers with different abundances (m1=0.1* p_1 +0.9* p_2; m2= 0.2* p_1 +0.8* p_2; m3= 0.3* p_1 +0.7* p_2, , m4=0.1* p_2 +0.9* p_1; m5= 0.2* p_2 +0.8* p_1 and m6=0.3* p_2 +0.7* p_1). The results of the classification are shown in Table 2.

	M1	*m2*	*m3*	*m4*	*m5*	*M6*
Class.	2	2	2	1	1	1

Table 2. Mixture classification.

The weights stored in the SOM neurons are higher correlated with the corresponding endmembers.
The noise influence has been proved by corrupting the endmember with different noise ratio percentage; the endmember are learned correctly by the SOM when the number of output neurons are the same that the number of endmembers.
When this number exceeds the number of endmembers, some neurons have redundant information. Only one of these neurons can remain; the weight vector of the others must be initialized with the hyperspectral signatures of some spatially selected pixels on the image.

5 Summary and Conclusions

We have improved an hyperspectral neural tool with a S.O.M. layer. The new tool resolves adequately hyperspectral images to make easier the endmember extraction.
Most of the known methods need a careful human supervision. This proposed method uses an unsupervised process, being this it main advantage.
The algorithm is robust with the noise-ratio percentage and it extracts adequately the endmember in mixture signatures.

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