A Neural Network Method of Selective End-member for Pixel Unmixing

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Abstract: Remote sensing images contain a lot of mixed image pixels, but it is difficult to classify these pixels. If the number of pixel’s end-member is regarded as unchangeable, the traditional pixel unmixing algorithm cannot get a good result. In this paper we develop a new method of selective end-members for pixel unmixing based on the fuzzy ARTMAP neural network, which firstly compares the pixel’s spectral to the conference one and then gets the number of end-member. When it is taken into account, we use an ARTMAP neural network to extract subpixel information. Finally, experimental results show that the selective end-member algorithm achieves improvement over conventional ANN algorithms and conventional linear algorithms.

Key Words: mixed pixel, selective end-member, linear algorithm, ANN, Fuzzy ARTMAP

1. Introduction

A common problem in remote sensing is that the limited spatial resolution of the scanner inevitably leads to “mixed” pixels at class boundaries. That is, individual pixels cover more than one ground cover type\cite{1}. This leads to the spectral response at a pixel being a mixture of the underlying pure classes—the so-called end-members. The traditional classification process is to assign a label to each pixel; this can be a problem for a mixed pixel since it does not exclusively belong to any single class. Obviously, if the target’s size is smaller than the resolution of the image, it cannot be seen directly. However, through the proper use of the information in the spectral domain, it is possible to infer the pure components and their fractions in the mixed pixel. Pixel unmixing is the decomposition of mixed pixels into a collection of distinct end-members and a set of fractional abundances that indicate the proportion of each end-member in the mixed pixel. In the past decade, several different unmixing models have been implemented, including neural networks\cite{2}, fuzzy classifiers\cite{3}, regression and decision trees\cite{4}, Gaussian mixture discriminate analysis\cite{5}. The non-linear model, that is neural network based model, outperformed the traditional linear unmixing model. It can capture non-linear effects and thus performs better than the conventional linear unmixing models, but the number of the end-member can not change during the process of pixel unmixing, so in this paper a new procedure to overcome the problem has been tested, the method is based on a dynamic identification of the optimum end-member subset for each pixel, selected from a larger number of typical end-members, this subset of potential end-members is then used for a conventional ARTMAP model unmixing of the pixel.
2. Methodology

A. Fuzzy ARTMAP Model

The Adaptive Resonance Theory (ART) family of pattern recognition algorithms was developed by Carpenter and Grossberg\[^{[6]}\]. ART is a match-based learning system, the major feature of which is its ability to solve the “stability–plasticity dilemma” or “serial learning problem”, where successive training of a network interferes with previously acquired knowledge. Among the ART family models, fuzzy ARTMAP is a supervised learning system that has been used widely in many fields\[^{[7]}\]. A comprehensive description of the model is detailed in Carpenter et al. from which the synopsis of the basic architecture of the fuzzy ARTMAP model is drawn (Fig. 2). It consists of a pair of fuzzy ART modules, ART\(_a\) and ART\(_b\), connected by an associative learning network called Map Field. The architecture uses a learning rule that minimizes the training error (to reduce bias) while concurrently minimizing the testing error (to reduce the combination of bias and variance). The ARTMAP model has two important parameters, vigilance value for both ART\(_a\) (\(q_a\)) and ART\(_b\) (\(q_b\)), which controls the generation of “hidden units”. The “hidden units” in ART\(_a\) and ART\(_b\) are called F2 nodes, which represent learned recognition categories. Each category (cluster or F2 node) extracts and generates common spectral properties (ART\(_a\)) and class mixture information (ART\(_b\)) from training data.

In this study, the spectral values associated with the ETM scale pixels form the input vector for ART\(_a\) and land cover proportions associated with the ETM pixel form the input vector for ART\(_b\). During training, ARTMAP is presented with a stream of ART\(_a\) and associated ART\(_b\) pairs of inputs. During testing, a stream of ART\(_a\) inputs is presented and the network predicts the associated class proportions through ART\(_b\).

![Figure 1 Architecture of ARTMAP neural network](image)

B. Proposed unmixing algorithm

In the conventional method, whatever the pixel unmixing model is linear or non-linear, the number of the end-member \(N\) is regarded as unchangeable, but in fact, that is not truth, the number will be changed when each different pixel is selected. An efficient strategy to overcome the condition of identifiability when the number of bands is fixed is the selection of the most representative end-members within a larger set prior to scene decomposition\[^{[8]}\]. A cross correlogram is constructed by calculating the cross correlation coefficient between a test spectrum (a pixel spectrum) and a referenced spectrum (a laboratory or pixel spectrum known to characterize a mineral of interest) at different match positions. After the selection, all remaining spectral components are discarded and can no longer be considered. If we denote the test and
reference spectrum as $R_r$ and $R_t$ respectively, $n$ is the number of overlapping positions, the cross correlation for match position can be calculated as the below formulation:

$$r = \frac{n \sum R_r R_t - \sum R_r \sum R_t}{\sqrt{\left[n \sum R_r^2 - (\sum R_r)^2\right] \cdot \left[n \sum R_t^2 - (\sum R_t)^2\right]}}$$  \hspace{1cm} (1)

Each candidate pixel is projected onto all available normal end-member vectors, and the most efficient projection, which corresponds to that with the highest value, indicates the first selected end-member. The spectral signal of this is then orthogonally subtracted from that of the pixel by

$$\rho_r = \rho - r_{\text{max}} A_{\text{max}}$$  \hspace{1cm} (2)

Where

- $\rho_r$: vector with the residual pixel spectral signature;
- $r_{\text{max}}$: normal spectral vector with maximum projection.

The residual pixel signature is then used to identify the second end-member to select by repeating the projection onto all remaining end-member normal vectors. The process can continue up to the identification of a complete subset with a prefixed maximum number of end-members or stopped whenever no projection reduces the residual spectral signature significantly. Some pixels of the scene will stop iteration only once, and the parameter $\rho_r$ can satisfy the condition, so it proved that the end-member vectors of these pixels are Non-Orthogonal, we can add an adjustive parameter $\eta$ taken value (0,1) as follows:

$$\rho_r = \rho - \eta r_{\text{max}} A_{\text{max}}$$  \hspace{1cm} (4)

There are two different situations: (1) If it get a large value, termination will happen after several iterative processes, that could not measure up; (2) If it get a small value, the end-member number contains unchangeable, whatever the above conditions happened, the result value is inaccurate. In this way, the selected subset will contain the components that are most suited to decomposing the candidate pixel by subsequent usual linear pixel unmixing. The two-step procedure, when applied to all pixels, will eventually produce normal abundance images for all number of components end-members considered.

So the pixel unmixing algorithm is detailed as follows:

Step1: Pick out the end-member of components in the scene, and take them as the reference spectral, in the whole image compute the cross correlation spectral match value and line up $r$ based on equation (1)–(4)

Setp2: Get the number of endmember, take it into account of the pixel unmixing equation, set up different ARTMAP models, in which the output layers is changed as the number, The else node of the ANN is set as 0.

Step3: Unite the result image using ANN models, get the abundance image of the whole scene.

3. Experimental Result

A ETM image is selected in Chang-jiang San Xia area of the Hubei province, which is obtained on April 21, 2002. The image is false color composite of TM band 1,2,3 covering the study area. (fig.2) The number of the end-member can be found approximately by MNF transform method \(^{(0)}\) (fig.3). In ENVI the data of the image is processed and the characters are
picked up, from the figure 3, obviously there are almost four types found, which are Chang-jiang river, urban land, vegetation and lake, because of the different spectral characters, the Chang-jiang river and the lake are distinguished as two types.

The methodologies mentioned in this paper are tested in the remote-sensing data sets. Three different pixel unmixing results are expressed, and the abundance images as follows:

Examples of abundance images (a)–(d), obtained by the conventional pixel unmixing processes. Choose parameter $\alpha = 10^{-6}$, vigilance parameter $\rho_a = 0$, and $\rho_b = 0.8$, matching parameter $\varepsilon = 0.01$, in the initialization of the ARTMAP model, after the processes the results are shown in figure 3 (e)–(h). In the proposal approach, different with above, firstly we must get the number of the end-members, then there are four conditions including: 1) If $N=1$, the kind of these pixels are put into directly, there is only one component in the pixel, other else equal to 0; 2) If $N=2$, in ARTMAP model the number of the output layer is set as 2, and there are six different forms to train and test; 3) If $N=3$, in ARTMAP model the number of the output layer is set as 3, and there
are four different forms to train and test; 4) If N=4, the pixel’s components are saturated, and these unmixed pixels satisfied this condition are just like the common ANN directly unmixed., the abundance images as follows in fig3 (i)−(l).

From the abundance images, the brighter pixels represent the higher proportion, and vice versa. So in order to compare each of these conveniently, the end-member of the four kinds is ensured unchangeable. As can be seen, the abundance images from the three procedures were rather different, with more spatial variability retained by the new approach, while the conventional process obviously tended to confuse all vegetation and urban land types. In the four abundance areas, some regions which is regarded as pure area, just like the Changjiang river, are same as each others, but in the mixed area, as can be seen, the difference is obviously. For test the advantages of the proposal approach, the pure area is chosen, which has 400 pixels, the differences are discriminated and the mean abundance value as follows:

<table>
<thead>
<tr>
<th>Table.1 The results of unmixing</th>
<th>Changjiang river</th>
<th>Urban land</th>
<th>Vegetation</th>
<th>Lake</th>
</tr>
</thead>
<tbody>
<tr>
<td>Line unmixing</td>
<td>0.82178</td>
<td>0.03130</td>
<td>0.03315</td>
<td>0.1137</td>
</tr>
<tr>
<td>ARTMAP</td>
<td>0.83568</td>
<td>0.03977</td>
<td>0.01213</td>
<td>0.1124</td>
</tr>
<tr>
<td>The proposal algorithm</td>
<td>0.90370</td>
<td>0</td>
<td>0</td>
<td>0.0963</td>
</tr>
</tbody>
</table>

These results give a first indication of the efficiency of the new approach, but a more direct evaluation of the correctness of the unmixing outputs was also necessary. So we get the ground truth value to evaluate the unmixing result, the previous three tests are therefore repeated on the new scene and the mean residual errors were computed. As a consequence, the mean residual error of the new method was lower than that of the conventional ones in table 2.

<table>
<thead>
<tr>
<th>Table.2 The comparison of RMSE</th>
<th>Changjiang river</th>
<th>Urban land</th>
<th>Vegetation</th>
<th>Lake</th>
</tr>
</thead>
<tbody>
<tr>
<td>Line unmixing</td>
<td>0.0811</td>
<td>0.3150</td>
<td>0.2845</td>
<td>0.1249</td>
</tr>
<tr>
<td>ARTMAP</td>
<td>0.0653</td>
<td>0.1258</td>
<td>0.2476</td>
<td>0.1013</td>
</tr>
<tr>
<td>The proposal algorithm</td>
<td>0.0610</td>
<td>0.0986</td>
<td>0.1013</td>
<td>0.1002</td>
</tr>
</tbody>
</table>

4. Conclusion

This paper has presented selective end-member of fuzzy ARTMAP model which makes use of the nonlinear characteristics of spectral mixture to obtain the higher unmixing accuracies by suggesting a two step procedure. The selection of the optimum end-member subset is carried out independently for each pixel by simple operations based on the CCRS, this is an important requisite for the success of the subsequent unmixing process, which accomplishes perfect results for all the materials with RMS error. The comparative experiments show that the proposed algorithm slightly outperforms than linear pixel unmixing and directly ARTMAP model as a whole.

References


