Classification of CBERS-2 Imagery with Fuzzy ARTMAP Classifier

LUO Chengfeng  LIU Zhengjun  YAN Qin

Abstract  A fuzzy ARTMAP classifier is adopted for a classification experiment of CBERS-2 imagery. The fundamental theory and processing about the algorithm are first introduced, followed with a land-use classification experiment in Shihezi County on CBERS-2 high resolution imagery. Three classifiers are compared: maximum likelihood classifier (MLC), error back propagation (BP) classifier, and fuzzy ARTMAP classifier. The comparison shows comparably better results for the fuzzy ARTMAP classifier, with overall classification accuracy of 9.9% and 4.6% higher than that of MLC and BP. The results also prove that the fuzzy ARTMAP classifier has better discernment in identifying bare soil on CBERS-2 imagery.

Keywords  fuzzy ARTMAP; CBERS-2 imagery; classification

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Introduction

It has been proven by many studies that a neural network classifier is superior to conventional ones in classifying remote sensing data, and the total accuracy would be improved by 10%-20%[1]. BP is the most prevalent and universal neural network arithmetic[2]. BP and its transformations have been widely adopted as classifiers for remote sensing data applications. But before working, the user has to choose some parameters[3], such as BP network architecture, learning speed, etc., which have an effect on training time, execution and convergent speed. Moreover, a BP neural network is limited when it comes to auto-adaptation and auto-normal.

Fuzzy adaptive resonance theory map (fuzzy ARTMAP), which was proposed by Carpenter in 1992, is made up of two fuzzy ARTs[4]. It can learn and identify things at high speeds and in real-time by classifying input vectors according to the most analogical pattern saved. In 1994, Gopal[5] adopted the algorithm to classify AVHRR1.1-km data and had an accuracy about 20% better than the BP neural network classifier; in 1997, Fischer[6] classified TM data with the algorithm and had an accuracy above 95%. This paper studied the classification of CBERS-2 (China-Brazil Earth Resource Satellite, launched by China) data with the fuzzy ARTMAP.

1  Methodology

The fuzzy ARTMAP achieves a synthesis of fuzzy logic and adaptive resonance theory between the computations of subsets and ART category choice, resonance, and learning[4]. The architecture involves two fuzzy MAP[7] models ARTa and ARTb, which are linked by an inner ART model $F_{ab}$, also named as the map field.
1.1 Preprocessing input vector

On the assumption that there are $M$ bands and $N$ categories with the source remote sensing image, the input sample vector for ART$_a$ is $a = [a_i, a_2, \ldots, a_M]$, $a_i \in [0, 1], i = 1, 2, \ldots, M$, after normalization and complement coding, and vector $A$ can be achieved from $a$, where $A = [a^a] = [a_1, a_2, \ldots, a_M] \in [0, 1]^M$, $a_i = 1 - a_i, 1 \leq i \leq M$. For every input vector $A = [a^a]$, there is $\|A\| = \|(a^a)\| = \sum_{i=1}^{M} a_i + (M - \sum_{i=1}^{M} a_i) = M$. The objective categories of the sample are the input vector for ART$_a$, that is $b = [b_1, b_2, \ldots, b_N]$, $b_j = 0$ or 1, $\sum_{j=1}^{N} b_j = 1$, and $j = 1, 2, \ldots, N$. Similar to the relationship between $a$ and $A$ mentioned above, the $B$, input vector for ART$_b$, is out of vector $b$. Vector $a$ and $b$ is an input pair.

1.2 Initializing network

For ART$_a$, let $x^a = [x_{1a}^a, \ldots, x_{2Ma}^a]$ denote the $F^a$ output vector, let $y^a = [y_{1a}^a, \ldots, y_{2Ma}^a]$ denote the $F^a$ output vector, and let $w^a = [w_{1a}^a, w_{2a}^a, \ldots, w_{2Ma}^a]$ denote the $j$th ART$_b$ weight vector. For ART$_b$, let $x^b = [x_{1b}^a, \ldots, x_{2Nb}^a]$ denote $F^b$ output vector, let $y^b = [y_{1b}^x, \ldots, y_{2Nb}^x]$ denote $F^b$ output vector, and let $w^b = [w_{1b}^x, w_{2b}^x, \ldots, w_{2Nb}^x]$ denote the $k$th ART$_b$ weight vector. For $F^ab$, let $x^ab = [x_{1b}^a, \ldots, x_{2Nb}^a]$ denote $F^ab$ output vector, and let $w^ab = [w_{1b}^ab, w_{2b}^ab, \ldots, w_{2Nb}^ab]$ denote the weight vector from the $j$th $F^a$ node to $F^ab$.

Fuzzy ARTMAP dynamics are determined by a choice parameter $\alpha > 0$, a learning rate parameter $\beta \in [0, 1]$, vigilance parameters $\rho_a \in [0, 1]$, $\rho_b \in [0, 1]$ and match tracking parameter $\epsilon$. The initial values of the weight vector obey

$$W_{ij} \equiv 1, i = 1, 2, \ldots, 2M; \; j = 1, 2, \ldots, L$$

$$W_{jk} \equiv 1, j = 1, 2, \ldots, L; \; k = 1, 2, \ldots, N$$

(1)

where $M$ is the dimension of the input vector $a$; $L$ is the coded node number of $F^a$; and $N$ is the dimension of the output vector $b$.

1.3 Map field activation and match tracking

For each input vector $I$ and $F^a$ node $j$ (including $A$ and $B$), the choice function $T_j$ is defined by:

$$T_j(I) = \frac{I \cap w_j}{\alpha + |w_j|}$$

(2)

The function used to select the $F^b$ winning node is defined by:

$$T_j = \max \{T_j; \; j = 1, \ldots, N\}$$

(3)

and the category choice is indexed by $J$; if more than one $T_j$ is maximal, the category $j$ with the smallest index is chosen. Resonance occurs if the following equations are met.

$$|A \cap w_j| \geq \rho_a |A|$$

(4)

$$|y^b \cap w_j^ab| \geq \rho_b |y^b|$$

(5)

At the same time, $x^ab = y^b \cap w_j^ab$; otherwise the node mismatch reset occurs if Eq.(4) could not be met, and $x^ab = y^b$. The value of the choice function $T_j$ is set to 0 for the duration of the input presentation to prevent the persistent selection of the same category during search. The search process continues among the left nodes using the same judgment mentioned above; if Eq.(4) is met but Eq.(5) is not, match tracking begins and $\rho_a$ will increase $\epsilon$ based on $|A \cap w_j|/|A|$. Search will continue with a new vigilance parameter to find the winning node in $F^a$. If no such node exists, we shut down $F^a$ for the remainder of the input presentation.

1.4 Map field learning

Once a search ends, the weight vector is updated according to the following equations:

$$W^b_{ij}(new) = \beta(A \cap W^a_{ij}(old)) + (1 - \beta)W^b_{ij}(old), i = 1, 2, \ldots, 2M$$

(6)

$$W^ab_{jk}(new) = \beta(A \cap W^ab_{jk}(old)) + (1 - \beta)W^ab_{jk}(old), k = 1, 2, \ldots, N$$

(7)

where $W^a_{ij}(old)$, $W^ab_{jk}(old)$ and $W_i^b(\text{new})$, $W^ab_{jk}(\text{new})$ represent the old and revised weight vectors of the $J$th node. It is useful to set $\beta = 1$ when $J$ is an uncommitted node (uncommitted nodes are those that never win or win without resonance; the committed nodes are those that win with resonance), that is fast learning; and then to take $0 < \beta < 1$ after the category is committed. Different $\beta$ values mean that the last weight vector has different effect on the new weight, and the weight vectors for $j \neq J$ nodes remain unchanged. $\rho_a$ is reset to be the initial value after
learning, then the next input sample learning begins. Once the \( J \)th node in \( F^b_2 \) learned the \( K \)th category in \( F^b_2 \), the weight vector for map field \( F^{ab} \) changes:

\[
W^{ab}_{jk} = \begin{cases} 
1, & j = J, k = K \\
0, & j \neq J, k \neq K 
\end{cases}
\]

\hspace{1cm} (8)

The trained fuzzy ARTMAP architecture is the basis for classifying remote sensing imagery; and for pixel, with the input vector coming from values in every band. The optimal pattern was found from the trained patterns in \( ART_a \), and the category corresponding to the pattern is in the class of the pixel.

2 Data and preprocessing

CBERS-2 data used in the study were completed on September 13, 2004, and the study area is Shihezi County, Xinjiang. The area lies in the middle of the foot of north Tianshan Mountain, north Junger Basin, and south Gurbandungtug Desert. The main land cover classes are Gobi and local bare land, and the central region is a plantation. Quality of the land, which is encrusted with salt badly without enough water, has been deteriorating. Four bands are selected as input parameters: 0.45-0.52 \( \mu \)m, 0.52-0.59 \( \mu \)m, 0.63-0.69 \( \mu \)m and 0.77-0.89 \( \mu \)m, the resolution is 19.5 m. The combined surface and atmospheric reflectance of the Earth\([8, 9]\) is computed as input based image DN value. The reflectance is between 0 and 1, which also meets the input vector need for fuzzy ARTMAP. The reflectance is computed as

\[
\rho = \frac{\pi \times L \times D^2}{E_{sun} \times \cos \theta}
\]

where \( \rho \) is unit-less planetary reflectance; \( L \) is spectral radiance at the sensor’s aperture (W/m\(^2\)·sr·\( \mu \)m); \( D \) is Earth-sun distance in astronomical units; \( E_{sun} \) is mean solar exoatmospheric irradiances (W/m\(^2\)·\( \mu \)m); and \( \theta \) is solar zenith angle in degrees.

The test image size is 2048 pixels \times 2048 pixels (Fig1(a)), and 6 classes: water, salina land, dry plantation, irrigable land, bare land, and sand. 750 samples are selected from the image for train referencing the land use map. Jeffries-Matusita\([10]\) distance (range 0-2) is adopted to measure the separability between different classes. Generally, a value more than 1.8 means good separability, and among our samples the lowest separability is 1.977 between bare land and sand, which shows that the samples are typical.

3 Results and analyses

The experiment was done with three classifiers: MLC, BP classifier, fuzzy ARTMAP, and their results were compared. MLC is one of several classic supervised algorithms that classifies with probability computed statistically. The samples remain consistent for three algorithms, and Fig.1(b) 1(d) show different classification results. From the results, the differences are obvious in three classes: sand, bare land, and salina land. Looking at the bottom-right part, the main class is salina land in Fig.1(b), sand in Fig.1(c), and bare land in Fig.1(d). In fact, the main class should actually be bare land, as it shows in the source image and reference map, moreover there also distributes many bare land samples. The difference of area percent is also apparent. The area comparison of different classification results is shown in Fig.2, and the result with MLC enlarges the percentage of salina land; for the BP result, the percentage of sand is much higher than bare land, which can be found form the resource image where it mistakenly identified bare land among dry plantations for sand.

There are 302 samples selected randomly to evaluate the classification accuracy. For different classification results three accuracy parameters - single class accuracy, total accuracy and total kappa coefficient\([11]\) - were compared. All the classification accuracy parameters of fuzzy ARTMAP were better than those of the other two results. The total accuracy for fuzzy ARTMAP is 97.70% and better than BP by 4.6%.

| Land use class   | MLC  | BP    | ARTMAP |
|------------------|------|-------|--------|
| Water            | 100.0% | 100.0% | 100.0% |
| Sand             | 76.92% | 93.42% | 94.23% |
| Bare land        | 88.00% | 82.00% | 95.83% |
| Dry plantation   | 82.00% | 94.00% | 98.00% |
| Irrigable land   | 86.54% | 92.31% | 98.08% |
| Salina land      | 95.27% | 90.20% | 96.08% |
| Total accuracy   | 88.82% | 93.09% | 97.70% |
| Kappa coefficient| 0.866 | 0.917 | 0.972 |
4 Conclusions

From the classification results it can be proven that a fuzzy ARTMAP offers better accuracy, including single class accuracy, total accuracy and total kappa coefficient, than MLC and BP on CBERS-2 imagery. The result also proved that a fuzzy ARTMAP classifier has better discernment to identify bare soil. The training speed and astringency of fuzzy ARTMAP are all better than those of BP. The fuzzy ARTMAP algorithm avoids revision of the network pattern classified, and can add a new pattern to suit new input automatically. The memory capacity increases with sample patterns, and its functions of fuzzy logic, automatic adaptation, and learning a new pattern is basic to improving classification accuracy and executive efficiency. It is difficult to confirm the architecture parameter, which depends on experience and experiment. Fixing the parameter is ideal for the efficiency of training and classification.

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