Landsat Satellite Image Segmentation Using the Fuzzy ARTMAP Neural Network

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Abstract

This application illustrates how the fuzzy ARTMAP neural network can be used to monitor environmental changes. A benchmark problem seeks to classify regions of a Landsat image into six soil and crop classes based on images from four spectral sensors. Simulations show that fuzzy ARTMAP outperforms fourteen other neural network and machine learning algorithms. Only the k-Nearest-Neighbor algorithm shows better performance (91% vs. 89%) but without any code compression, while fuzzy ARTMAP achieves a code compression ratio of 6:1. Even with a code compression ratio of 50:1 fuzzy ARTMAP still maintains good performance (83%). This example shows how fuzzy ARTMAP can combine accuracy and code compression in real-world applications.

Fuzzy ARTMAP

ARTMAP is a neural network architecture that performs incremental supervised learning of recognition categories and multidimensional maps in response to input vectors presented in arbitrary order. The first ARTMAP system (Carpenter, Grossberg, & Reynolds, 1991) was used to classify inputs by the set of features they possess, that is, by a vector of binary values representing the presence or absence of each feature. The more general fuzzy ARTMAP system (Carpenter, Grossberg, Markuzon, Reynolds, & Rosen, 1992) learns to classify analog or binary inputs, by replacing the ART 1 modules (Carpenter & Grossberg, 1987) of binary ARTMAP with fuzzy ART modules (Carpenter, Grossberg, & Rosen, 1991). Fuzzy ARTMAP achieves accuracy, speed, and code compression in both on-line and off-line settings. It has a small number of parameters, requires no problem-specific system crafting or choice of initial weight values, and does not get trapped in local minima. In addition, fuzzy ARTMAP has shown better performance than various other neural networks in a rapidly expanding set of benchmark studies. Examples of successful ARTMAP applications include automatic analysis of electrocardiograms (Ham & Han, 1993; Suzuki, Abe, & Ono,

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1993), diagnostic monitoring of nuclear plants (Keyvan, Durg, & Rabelo, 1993), prediction of protein secondary structure (Metha, Vij, & Rabelo, 1993), and computer-aided airplane design (Caudell, Smith, Escobedo, & Anderson, 1994). Variations of ART and ARTMAP networks have also been applied for analysis of large medical databases (Carpenter & Tan, 1993; Harvey, 1993), 3-D object recognition using spatial and temporal evidence accumulation (Seibert & Waxman, 1991, 1992; Carpenter & Ross, 1993; Bradski & Grossberg, 1994), robot navigation (Dubrawski & Crowley, 1994; Bachelder, Waxman, & Seibert, 1993; Baloch & Waxman, 1991), analysis of musical structure (Gjerdingen, 1990), air quality monitoring (Wienke, Xie, & Hopke, 1994), military target recognition (Moya, Koch, & Hostetler, 1993), multi-variable optimization of high performance concrete mixes (Kasperkiewicz, Racz, & Dubrawski, 1994), and multi-sensor data fusion (Asfour, Carpenter, Grossberg, & Lesher, 1993). Fuzzy ARTMAP is here applied to the analysis of remote sensing images, learning to identify six soil and crop classes from portions of Landsat images. This benchmark database was used by Feng, Sutherland, King, Muggleton, and Henery (1993) to compare performance of fourteen other neural network and machine learning algorithms.

ARTMAP Dynamics

Each ARTMAP system includes a pair of Adaptive Resonance Theory modules (ART_a and ART_b) that create stable recognition categories in response to arbitrary sequences of input patterns (Figure 1). During supervised learning, the ART_a module receives a stream $\{\mathbf{a}^{(l)}\}$ of input patterns and ART_b receives a stream $\{\mathbf{b}^{(l)}\}$ of input patterns, where $\mathbf{b}^{(l)}$ is the correct prediction given $\mathbf{a}^{(l)}$. These modules are linked by an associative learning network and an internal controller that ensures autonomous system operation in real time. The controller is designed to create the minimal number of ART_a recognition categories, or "hidden units," needed to meet accuracy criteria. It does this by realizing a *minimax learning rule* that enables an ARTMAP system to learn quickly, efficiently, and accurately as it conjointly *minimizes* predictive error and *maximizes* code compression. Predictive success is automatically linked to category size on a trial-by-trial basis using only local operations, through increasing the vigilance parameter (ρ_a) of ART_a by the minimal amount needed to correct a predictive error at ART_b. Vigilance ρ_a calibrates the minimum confidence that ART_a must have in a recognition category, or hypothesis, activated by an input $\mathbf{a}^{(l)}$ in order for ART_a to accept that category, rather than search for a better one (and perhaps establish a new category). Lower values of ρ_a enable larger categories to form, leading to a higher degree of code compression. A predictive failure at ART_b increases ρ_a by the minimum amount needed to trigger alternative hypothesis testing at ART_a, using a mechanism called *match tracking* (Carpenter, Grossberg, & Reynolds, 1991). Match tracking sacrifices the minimum amount of generalization necessary to correct a predictive error. The combination of match tracking and fast learning allows an ARTMAP system to learn a correct prediction of a rare event embedded in a cloud of featurally similar frequent events that make a different prediction.

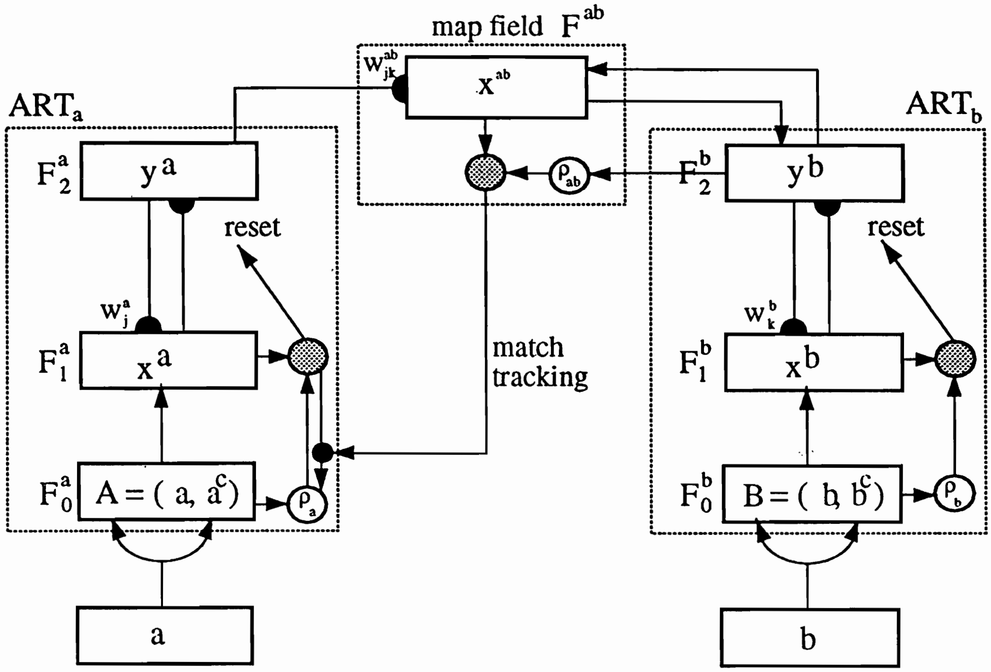

Figure 1: Fuzzy ARTMAP consists of two fuzzy ART modules ART_a and ART_b. The two modules are connected via a map field F^{ab} where associations between input and target categories are learned.

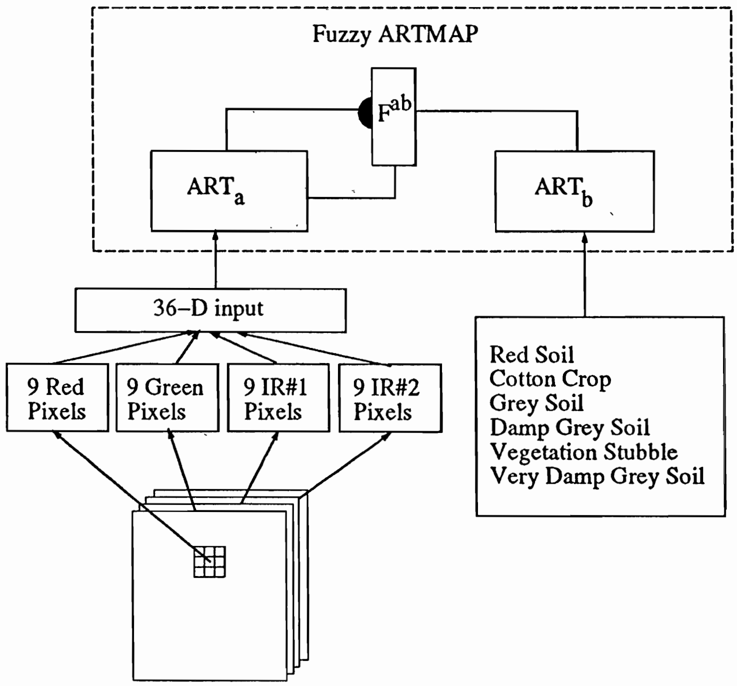

Figure 2: Fuzzy ARTMAP was used to classify Landsat image data by concatenating information from four spectral channels for each of nine pixels into a single 36-D feature vector.

Algorithm	*Accuracy(%)*
k-N-N	91
fuzzy ARTMAP	89
RBF	88
Alloc80	87
INDCART	86
CART	86
Backprop	86
C4.5	85

Algorithm	*Accuracy(%)*
NewID	85
CN2	85
Quadra	85
SMART	84
LogReg	83
Discrim	83
CASTLE	81

Table 1: In comparison to fourteen other algorithms, fuzzy ARTMAP achieves near optimal performance. The k-N-N algorithm is the only algorithm that outperforms fuzzy ARTMAP. However, fuzzy ARTMAP achieves 6:1 code compression, whereas the k-N-N does not compress information at all. (Adapted from Feng et al., 1993)

Algorithm	Test Set Performance	Categories Stored	Code Compression
k-N-N	91%	4,435	1:1
fuzzy ARTMAP ($\overline{\rho}_a = 0.9$)	89%	704	6:1
fuzzy ARTMAP ($\overline{\rho}_a = 0.0$)	83%	89	50:1

Table 2: Fuzzy ARTMAP performs almost as well as the k-N-N algorithm while achieving a 6:1 code compression ratio. When the baseline vigilance parameter $\overline{\rho}_a$ is reduced to 0, fuzzy ARTMAP achieves even higher compression while retaining good performance.

Landsat Image Data

The data used in this application are derived from a small section of Landsat satellite Multi-Spectral Scanner (MSS) frame (King, 1992). One frame of Landsat MSS imagery consists of four digital images of the same scene in different spectral bands. Two of these are in the visible region (corresponding approximately to green and red regions of the visible spectrum) and two are in the (near) infra-red. The database was generated by partitioning a small section (82 rows and 100 columns) of a Landsat MSS frame into several non-overlapping 3-by-3 pixel grids. Each pixel in the Landsat frame, which represents an 80m x 80m area, was classified into one of six vegetation classes (red soil, cotton crop, gray soil, damp gray soil, soil with vegetation stubble, and very damp gray soil) on the basis of a site visit. Feng et al. (1993) compare the performance of fourteen statistical and neural network classification algorithms on the database. Although performance might have been improved by appropriate preprocessing of the satellite image, only the normalized version of the raw pixel values was used for the fuzzy ARTMAP simulations in order to compare the results directly with the other methods benchmarked by Feng et al.

Fuzzy ARTMAP Performance

The database input consisted of a 36-D vector that was formed by concatenating the four spectral values of each pixel in the nine-pixel grid into a single feature vector. Fuzzy

ARTMAP was trained on the canonical 4,435 training set vectors until it achieved 100% accuracy on this set. Once training was complete, performance was tested on a disjoint set of 2,000 input vectors.

Simulations show that fuzzy ARTMAP can achieve near optimal performance when compared to fourteen other algorithms (Table 1). By setting the baseline vigilance to $\overline{\rho}_a = 0.9$, fuzzy ARTMAP achieves 89% predictive accuracy on the test set after ten epochs of training, while compressing the input data into 704 F_2^a categories, a 6:1 compression ratio. In contrast, the k-NN algorithm needs to store all inputs to achieve the best performance of all algorithms (91%).

Fuzzy ARTMAP can also achieve larger compression ratios while still maintaining respectable performance. By setting the baseline vigilance to $\overline{\rho}_a = 0.0$, fuzzy ARTMAP achieves an accuracy of 83%, while compressing the input data into 89 F_2^a categories, a 50:1 compression ratio. By manipulating a single parameter (the value of the baseline vigilance, $\overline{\rho}_a$) fuzzy ARTMAP can trade off between optimal performance, with some code compression, or very high code compression, with reasonable performance (Table 2).

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