FUZZY NEURAL MODEL FOR AERIAL IMAGE SEGMENTATION

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ABSTRACT: *This paper presents the segmentation of an aerial image gray scale image using Fuzzy Lattice Neural (FLN) model. Segmentation plays an important role in the process of digital image processing towards automatic extraction of GIS objects from aerial imagery. The FLN model is applicable to low quality imagery without traditional image preprocessing. The detection of buildings in aerial images is an important part of the automated interpretation of these data. As additional data like laser scan data is expensive and often simply not available, the presented approach is based only on aerial images. In this paper, a fuzzy clustering method based on fuzzy lattice neural network is presented. The image pixels of the aerial image use the FLN algorithm to segment the entire image. The success rate is high when fuzzy lattice neural network is used.*

Keywords: *Segmentation, Fuzzy Lattice, Neural Network, Aerial Image.*

AMS Subject Classification: *06D72, 62B5, 62H30.*

1. INTRODUCTION

Satellite imagery, a remote sensing technique, is convenient for large scale surveys, and has been used widely for land cover and habitat mapping using different applications [8], [14], but it has low resolution and it can be expensive to obtain timely imagery. Alternatively, aerial photography can provide higher resolution to allow monitoring of forest health and identification of tree species at an acceptable level of accuracy [10].

Image segmentation plays a key role in a wide range of applications, such as image visualization [16], image coding [3], [15], image synthesis [24], pattern recognition [26], [6] and so on. It is one of the first steps in an image analysis process and is of crucial importance. It is a process of partitioning an image into regions such that each region is homogeneous and at the same time none of the union of two adjacent regions is homogeneous.

There have been many different families of segmentation algorithms proposed in past years. These algorithms can be categorized into edge-based [17], clustering-based [19], [20], region-based [7] and split/merge [27], [28] algorithms. Among these algorithms, clustering-based algorithms are one of those proved to be suited for remotely sensed image segmentation.

Fuzzy segmentation algorithms try to cope with each cluster as a fuzzy set and each pixel in a image has a membership value (ranging between 0 and 1) associated to each cluster, measuring how much the pixel belongs to that particular cluster. In fuzzy segmentation algorithms, the most popular one is the Fuzzy C-means (FCM) algorithm [2] and many research works have been proposed to steep up the FCM algorithm [25], [5], [18]. Although the FCM algorithm is powerful in image segmentation, there is still a drawback encountered, that is the desired number of clusters should be specified in advance. This is a disadvantage whenever the clustering problem cannot specify any desired number of clusters. The situations are often for remotely sensed image segmentation, because the ground truth is always not available for these images.

In this paper, the fuzzy lattice concept is applied to segmentation. The data points that belong to a cluster are vague in nature. Hence the application of Fuzzy model has been proposed to incorporate the uncertainty of the classification results.

The paper is organized as follows: Section 2 briefs the concepts of fuzzy lattice neural network method. Section 3 discusses the application of fuzzy lattice neural model to segmentation. The experimental set up and illustrations are given in Section 4. Section 5 discusses the conclusion and future work.

2. FUZZY LATTICE NEUROCOMPUTING

A fuzzy lattice is a lattice that fuzzifies the conventionally binary valued lattice-inclusion relation $\leq$ which is applicable to any pair of lattice elements. A complete lattice is a lattice with a minimum and a maximum element denoted by 0 and 1 respectively.

The notion of fuzzy lattice has been introduced in [21], [22], [23] in order to extend the lattice ordering relation to all pairs $(x, y) \in L \times L$ of a crisp lattice L.

In [1] a valuation on a lattice L is defined to be a function f from L to the set of real numbers such that the following equality holds $f(x) + f(y) = f(x \wedge y) + f(x \vee y)$, where $\wedge$ and $\vee$ denote the lattice operations join and meet. A valuation is called positive if and only if $x < y$ in L implies $f(x) < f(y)$.

The concept of inclusion measure $\varphi(x, u)$ is a function from $L \times L$ to the interval [0, 1] that indicates the degree of truth of the lattice relation $x \leq u$. The function $\varphi(x, u) = \varphi(x \leq u)$ should satisfy the following three conditions:

(i) $\varphi(x \leq 0_L) = 0$ where 0_L is the least element in L.

(ii) $\varphi(u \leq u) = 1, \forall u \in L$.

(iii) $u \leq v \Rightarrow \varphi(x \leq u) \leq \varphi(x \leq v), \forall\, x, u, v \in L$ (Consistency property).

The positive valuation function f defined by $\varphi(x, u) = \dfrac{f(u)}{f(x \vee u)}$ is an inclusion measure. In our earlier work [12] and [13], the inputs are vectors of real numbers. The positive valuation $f(x)$ of $x = (x_1, x_2, \ldots, x_n)$ is defined by $f(x) = x_1 + x_2 + \ldots + x_n$. The join of $x = (x_1, x_2, \ldots, x_n)$ and $y = (y_1, y_2, \ldots, y_n)$ is taken as $x \vee y = \max(x, y) = \max(\max(x_1, y_1), \max(x_2, y_2), \ldots, \max(x_n, y_n))$ and the meet of x and y as $x \wedge y = \min(x, y)$.

In this work, the inputs are real numbers. We have defined the valuation function $f(x) = x$ and the join of x and y as $x \vee y = x + y$.

The fuzzy lattice neurocomputing has emerged as the combination of a theory of human cognitive information processing, that is the adaptive resonance theory or ART [4], with the mathematical theory of lattices [1] and with the theory of fuzzy sets [29]. It has been explained in [22] that both training and testing by FLN are effected the same way as by fuzzy-ART. Moreover well-known properties of learning by the fuzzy-ART neural model [9], [11] are retained by FLN.

Note that training by FLN requires two inputs, these are, a set S which includes all image pixels to be used for training as well as the vigilance parameter ρ which is the real number between 0 and 1. The output of training algorithm is a set of clusters, these are groups G_k, k = 1, ..., N which have been learned during training,

The clustering technique based on FLN is an unsupervised clustering method. The core of the algorithm lies in computing the degree of similarity of the elements in the pixel set X. The FLN model is constructed for segmentation. The names and roles of the various subsystems in Figure 1 are analogous to the names and roles of the corresponding

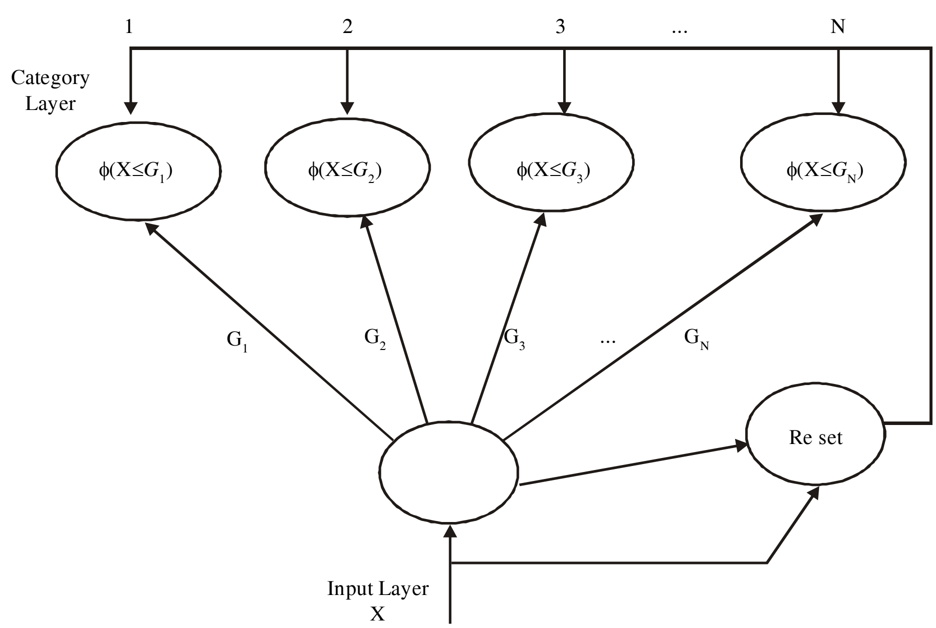

Figure 1: FLN Model

subsystems in an Adaptive Resonance Theory (ART) neural model as explained in [22]. The input vector of the network consists of pixels obtained from the image. Each pixel is a number between 0 and 255. The weight G_k, $k = 1, 2, ..., N$ of an interconnection in the FLN architecture in Figure 1 corresponds to a class consists of vector of numbers. A neuron in category layer of the FLN architecture computes the degree of inclusion of an input X to a weight G_k, $k = 1, 2, ..., N$ using an inclusion measure function $\varphi(X \leq G_k)$.

It is used as an activation function by the neurons of the upper layer of the two layer FLN neural architecture in Figure 1. It is a number in the interval [0, 1].

3. IMAGE SEGMENTATION

The grayscale image is considered for segmentation. The intensity values of the pixels of the image are real numbers. The pixels are arranged in ascending order and are applied to FLN model to segment the image. The first input, namely, pixel value is memorised in a group. Then the second pixel value x is compared with the memorized value u using the inclusion measure $\varphi(x, u) = \frac{u}{x \vee u}$. If its value is greater than the vigilance parameter ρ which lies between 0 and 1, then the pixel x will be in the first group. Otherwise it forms a new group.

In the same way, the next pixel value is compared with every group. The maximum inclusion measure of all pixels in a group is the membership value of that group. Among the groups, the maximum membership can be found and the pixel is in the maximum membership group if its membership satisfies the threshold value. After grouping the pixels, the image is segmented. Each group is the segment of the image. Algorithms for training and for testing using the FLN are described in the following:

Algorithm for Training

(i) Initially the input X_0 is stored in the memory. At an instant, there are N known classes $G_1, ..., G_N$ stored in the memory.

(ii) Present an input X to the initially set classes $G_1, \ldots, G_N$ where $G_k = \bigcup_i Y_{k,i}$ and is a vector of numbers.

(iii) Calculate $\varphi(X \leq G_k)$ for all G_k, $k = 1, ..., N$ that have not yet been 'reset' and $\varphi(X \leq G_k) = \varphi\left(X \leq \bigcup_i Y_{k,i}\right) = \max_i \varphi\left(X \leq Y_{k,i}\right)$.

(iv) Competition among the classes G_k : Select G_t such that $\varphi(X \leq G_t) = \max_k \varphi\left(X \leq G_k\right)$ where t is the index of corresponding winner and $G_t = \bigcup_i Y_{t,i}$.

(v) Assimilation condition : Whether $(\varphi(X \leq G_k) \geq \rho)$?

(vi) If the assimilation condition is successful, then X will be in the class G_t.

(vii) If the assimilation condition fails then reset G_t (i.e.) while the current input X is present, make G_t inaccessible during subsequent quests for a winner.

(viii) Completion test: Are all the classes $G_1, \ldots, G_N$ reset? If the completion test fails, go to step (iii) to look for another winner.

(ix) If the completion test is successful, then memorize X in G_{N+1}.

Algorithm for Testing

(i) Present an input D from the testing set to the classes.

(ii) Calculate $\varphi(D \leq G_k)$, $k = 1, ..., N$.

(iii) D belongs to the class G_t if $\varphi(X \leq G_t) = \max_k \varphi(X \leq G_k)$.

Note that the number N of clusters in category layer remains constant during testing.

The goal of clustering by FLN in the image has been to learn the clusters of pixels. The FLN scheme is presented in this work for application to lattice G of image pixels. We remark that neural computing based on the elements of an algebraic lattice, including the totally ordered lattice of real numbers, is a FLN's proposal.

4. EXPERIMENTAL SETUP

The color image is converted to gray scale image using MATLAB. The pixels of the image are applied to FLN model to segment the image. Each image size is 100 × 100 pixels. All 10000 pixel values are arranged in ascending order. Among the 10000 pixels, two third of the pixels are used as training data and the other one third are used as test data. The time required to train one FLN module on a Pentium IV system working at 3.06 Mhz with 512MB RAM was in the range of 1 seconds to 3 seconds depending on the problem.

Here we present results on two images. The images considered are 100 by 100 pixels each as shown in Figure 2 and Figure 3. Figure 2 is the aerial image for larger views of New Orleans, La., where flood waters consumed homes and cut off roadways. NOAA posted aerial images of the U.S. Gulf Coast areas that were decimated by Hurricane Katrina. Figure 3 is the Pentagon aerial image. During the Cold war, The Pentagon's strategic map of the world divided East from West. Figure 4 shows the segmented results of the image1 and Figure 5 shows the segmented results of the image2 using the FLN models which set the vigilance parameter $\rho = 0.625$

Figure 2: Image 1

Figure 3: Image 2

Figure 4: Image 1

Figure 5: Image 2

The FLN algorithm mentioned in the previous section has been implemented using C++. The data order dependence is a well-known property [23]. It should also be noted that data ordering has resulted in a shorter data processing time. In this work, the data are arranged in an ascending order and are fed to FLN algorithm to segment the image pixels. A large value of ρ within interval [0,1] implies more clusters. On the other hand as ρ decreases, fewer clusters are learned.

5. CONCLUSION

The FLN scheme has been presented in this work as a promising tool for image segmentation. In experiments, the proposed method demonstrated promising performance even in a complex environment. Due to the modular structure of the proposed approach, the knowledge base can be easily expanded to other situations. The accuracy in segmentation is very high compared to other models. The FLN model is the best method for larger amount of data, whereas Fuzzy equivalence relation method is useful only for smaller amount of data. Our future work is to apply FLN model for segmenting remote sensing satellite images. The above mentioned two models are compared in Table 1 as below.

Table 1
Comparison of Classification Models

Model	*Learning*	*Number of Clusters*	*Data*	*Accuracy*
Fuzzy Equivalence Relation model	Supervised	Determined automatically	Less amount of data	less
FLN model	Unsupervised	Determined automatically	Larger amount of data	more

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