International Journal of Advanced Research in

Electronics, Communication & Instrumentation Engineering and Development

Volume: 1 Issue: 1 08-Nov-2013,ISSN_NO: 2347 -7210

ARTIFICIAL IMMUNE SYSTEM IN REMOTE SENSING IMAGES

. K.ARCHANA[1], R.MONIKA[2],
DEPARTMENT OF INFORMATION TECHNOLOGY,
ANJALAI AMMAL MAHALINGAM ENGINEERING COLLEGE,
KOVILVENNI.
dreamskarchu@gmail.com ,srmonika93@gmail.com

ABSTRACT—*In this paper, some initial investigations are conducted to apply Artificial immune system(AIS) for classification of remotely sensed images. As a novel branch of computational intelligence, AIS has strong capabilities of pattern recognition, learning and associative memory, hence it is natural to view AIS as a powerful information processing and problem-solving paradigm in both the scientific and engineering fields. There were few papers concern applications of AIS in feature extraction/classification of aerial or high resolution satellite image and how to apply it to remote sensing imagery classification is very difficult because of its characteristics of huge volume data. Remote sensing imagery classification task by Artificial immune system is attempted and the preliminary results are provided. The experiment is consisted of two steps: Firstly, the classification task employs the property of clonal selection of immune system. The clonal selection proposes a description of the way the immune systems copes with the pathogens to mount an adaptive immune response. Secondly, classification results are evaluated by three known algorithm: Parallelepiped_Minimum Distance and Maximum Likelihood. It is demonstrated that our method is superior to the three traditional algorithms, and its overall accuracy and Kappa coefficient reach 89.80% and 0.8725 respectively.*

KEY WORDS:
Remote sensing, artificial immune system, pattern recognition, classification, immune algorithms.

1, INTRODUCTION

Drawing inspiration from the vertebrate immune system, a new research field of Artificial Immune Systems(AIS) is springing up. The vertebrate immune system is a rich source of theories and acts as an inspiration for computer-based solutions. Over the last few years there has been an increasing interest in the area of artificial immune system. AIS uses ideas gleaned from immunology in order to develop systems capable of performing tasks in various engineering applications. Although AIS has demonstrated its great values, few applications are reported in remote sensing. Therefore, in this paper, our aim is to employ AIS, a new tool of information analysis for remote sensing image classification. In remote sensing image classification, an key issue is to improve classification accuracy. Conventional statistical classifier, such as maximum likelihood,has been applied for remote sensing image classification for many years. However, these conventional multivariate statistical methods require nonsingular and class-specific covariance matrices for all classes. Because of the complexity of ground matters and the diversity of disturbance, these traditional classification methods often have the drawback of low precision. In order to overcome the shortcoming of conventional classifiers, artificial immune systems are applied to remote sensing image classification .Compared to the conventional statistical classifier, AIS classifier has the capacity of self-learning and high robust and the advantages of artificial immune systems lies in the following theoretical aspects. First, AIS are data driven self-adaptive methods in that they can adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model. Second, they are universal functional approximators in that AIS can approximate any function with arbitrary accuracy. Third, AIS are nonlinear models, which makes them flexible in modeling real world complex relationships. By Experiment, it shows that AIS classification algorithm has high classification precision and can be used in remote sensing image classification.

1.1, THE HUMAN IMMUNE SYSTEM:

The human immune system is a complex system of cells, molecules and organs that represent an identification mechanism capable of perceiving and combating dysfunction from our own cells and the action of exogenous infectious microorganisms. The human immune system protects our bodies from infectious agents such as viruses, bacteria, fungi and other parasites. Any molecule that can be recognized by the adaptive immune system is known as an antigen(Ag).The basic component of the immune system is the lymphocytes or the white blood cells. Lymphocytes exist in two forms, B cells and T cells. These two types of cells are rather similar, but differ with relation to how they recognize antigens and by their functional roles, B-cells are capable of recognizing antigens free in solution, while T cells require antigens to be presented by other accessory cells. Each of this has distinct chemical structures and produces many Y shaped antibodies form its surfaces to kill the antigens. Ab's are molecules attached primarily to the surface of B cells whose aim is to recognize and bind to Ag's.

The immune system possesses several properties such as self/non-self discrimination immunological memory, positive /negative selection, immunological network, clonal selection and learning which performs complex tasks.

2. ARTIFICIAL IMMUNE SYSTEM:

2.1 Definition:

Dasgupta'99: "Artificial immune systems (AIS) are intelligent and adaptive systems inspired by the immune system toward real-world problem solving". de Castro and Timmis: "Artificial Immune Systems (AIS) are adaptive systems, inspired by theoretical immunology and observed immune functions, principles and models, which are applied to problem solving"

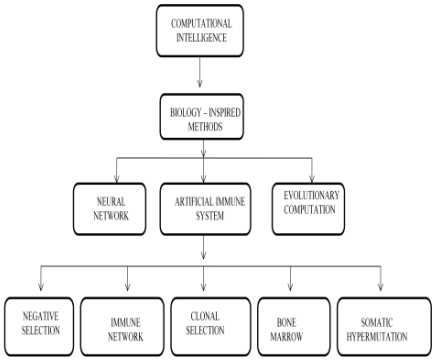

Fig.1 Hierarchical representation of Artificial immune system

2.2 Clonal Selection Theory:

In order to explain how an immune response is mounted when a non-self antigenic pattern is recognized by a B cell, clonal selection theory is been developed(F. M. Burnet, 1959). When a B-cell receptor recognizes a non-self antigen with certain affinity, it is selected to proliferate and produce antibodies in high volumes. The antibodies are soluble forms of the B-cell receptors that are released from the B-cell surface to cope with the invading non-self antigen. Antibodies bind to antigens leading to their eventual elimination by other immune cells. Proliferation in the case of immune cells is asexual, a mitotic process; the cells divide themselves. During reproduction, the B-cell clones undergo a hyper mutation process that, the Ag stimulates the B cell to proliferate and mature into terminal Ab secreting cells, named plasma cells. The process of cell division generates a clone. In addition to proliferating and differentiating into plasma cells, the activated B cells with high antigenic affinities are selected to become memory cells with long life spans. These memory cells circulate

through the blood, lymph, and tissues. When exposed to a second antigenic stimulus ,commence to differentiate into plasma cells capable of producing high-affinity Ab's, preselected for the specific Ag that had stimulated the primary response, Fig.2 illustrates the clonal selection, expansion, and affinity maturation processes.

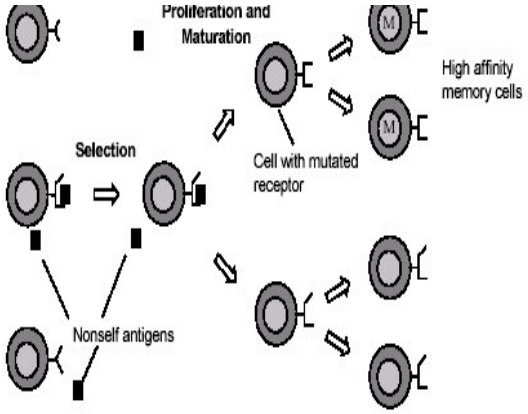

Fig.2 Clonal selection principle

2.3, Clonal Selection Algorithm(CLONALG):

L.N.De Castro, F..J. Von zuben developed the Clonal Selection Algorithm on the basis of clonal selection theory of the immune System. It was proved that can perform pattern recognition and adapt to solve multimodal optimization tasks. The CLONALG algorithm can be described as follows:

- Randomly initialize a population of individual(M);
- For each pattern of P, present it to the population M and determine its affinity with each element of the population M;
- Select n of the best highest affinity elements of M and generate copies of these individuals proportionally to their affinity with the antigen. The higher the affinity, the higher the number of copies, and vice-versa;
- Mutate all these copies with a rate proportional to their affinity with the input pattern: the higher the affinity, the smaller the mutation rate;
- Add these mutated individuals to the population M and reselect m of these maturated individuals to be kept as memories of the systems;
- Repeat steps 2 to 5 until a certain criterion is met.

3, ARTIFICIAL-IMMUNE CLASSIFICATION ALGORITHM:

Remote sensing image classification procedure involves two steps:

- First stage is the training of the system with a set of sample data.
- Generally, sample data is obtained by selecting the Region of Interest. In this paper, AIS is applied to train the sample data. After the training is complete, the remote sensing images are given for classification.

3.1 Training:

As explained above, the training is done wet a set of sample images. The sample images are obtained by selecting region of interest(ROI). To every region of interest. The training procedure is as follows:

- Initialization. Available Ab repertoire that can be decomposed into several different subsets. Let Ab{m} represent the set of memory cells. Ab{r} represent the set of remaining Ab. Ab =

Ab{m} + Ab{r}(r+m=N). This is done by randomly choosing training antigens to be added to the set of memory cells Ab{m} and to the set of Ab{r}. For each antigen Ag in the training set perform the following steps.

- Randomly choose an antigen *j Ag* in ROI and present it to all Ab's. Determine the vector *j aff* that contains the affinity of *j Ag* to all the N Ab's in Ab. For the current investigation, Euclidea distance *j d* is the primary metric of affinity. The Affinity *j aff* is defined as in equation(2) below:

$$dj = \sqrt{\sum_{i=1}^{bm} (xi-yi)2}$$

---------- (1)

$$aff_j = -d_j$$ ----------(2)

Where bm= the no. of remote sensing image bands.

- Select the nhighest affinity Ab's from Ab to compose a new set j n Ab{ } of high affinity Ab's in relation to j Agand In {m}Abfind the highest affinity memory cell, match mc.
- Clone the nselected Ab's based on their antigenic affinities, generating the clone set Cj. The higher the antigenic affinity, the higher the number of clones generated for each of the n selected Ab's. The total number of clones generated Nc is defined in equation(3) as follow:

$$N_c = \sum_{i=1}^{n} round(\beta . N / i)$$ ----------(3) where . = a multiplying facto

N = the total number of Ab's round

(·) = the operator that rounds its argument toward the closet integer.

- Allow each Ab's in clone set Cj the opportunity to produce mutated offspring *C* j*. The higher the affinity, the smaller the mutation rate. Where mutate procedure and function mutate(x) are defined in Figure 3. In Figure 3, the function Irandom() returns a random value in the range [0,1] and Lrandom returns a random value in the range [-1,1].Function _(t, y) is defined in equation(4) as follows:

$$\Delta(t, y) = y\,(1 - r^{(1-t/T)\lambda})$$ ---------- (4)

Where*t* = the iteration number

T=the maximum of iteration number

r =a random value in the range [0,1]

- =a parameter to decide the nonconforming degree

```
mutate(x)
{
foreach(x.vi in x.v)
do
ai= minvi
bi= maxvi
rd_mr = Irandom()
rd_to = Lrandom()
if(rd_mr < mutation_rate)
if (rd_to >= 0)
x.vi = x.vi + _(t, bi - x.vi )
else
x.vi = x.vi - _(t, x.vi –ai)
done
return x
}
```

Fig.3. Mutation

- Calculate the affinity *j affof the matured clones *C* j* in relation to antigen jAg.
- Select the highest affinity from the set of *C* j* in relation to jAgas the candidate memory cell, candidate mc, to enter the set of memory antibodies {m}Ab.
- Decide whether the candidate mcreplaces match mcthat was previously identified. If candidate mchas more affinity by the training antigen,ag, The candidate memory cell is added to the set of memory cells {m}Aband replace match mc.
- Replace the d lowest affinity Ab's from {r}Ab.
- A stopping criterion is calculated at this point. It is met if the average affinity for Ab's is above a threshold value. If the stopping criterion is met, then training on this one antigen stops. If the stopping criterion has not been met, repeat, beginning at step 3. This process continues until all antigens have been training.

3.2 Classification:

After training has completed, the evolved memory cells Ab{m} are available for the use for classification. Each memory cell is presented with a data item. By calculating the affinity between memory cell and image data, the image is classified into the class that has the maximum affinity.

4, EXPERIMENTAL RESULTS:

4.1 Data:

The study area of this research is in WUHAN city in China. The TM images (400×400 pixels) used were acquired in Oct.26 1998. Fig.4.shows the image. The classification patterns adopted here are five classes: Changjiang River, lake,vegetation, road and building. In the experiment, five regions of interests representing the five classes respectively were selectedfor training regions and every training region had 100 ground reference sample points.

Fig.4 WUHAN TM original image

4.2 Results:

In this case, the running parameters were n= 10, d=5 and _= 10. Fig.5 illustrates the classification result using Artificial Immune classifier. In order to compare the classification result, Fig.6 illustrates the classification result using maximum likelihood classifier. Table1 shows the classification accuracy and the Table 2 is the accuracy of the AIS method. From the table 2, it is found that AIS approach produces better classification results than the Maximum Likelihood method. In order to check theresults in more detail, we show confusion matrices in Table 1 and Table2. As shown in Table 2, the AIS approach improvedoverall classification accuracy from 85.0% to 89.8%(4.8% improvement). For each class, the vegetation has the largestimprovement from 59% to 76%(17% improvement), followed by road (5% improvement), building (4% improvement). Thereason for this is that the maximum likelihood approach works well only when the underlying assumptions are satisfied andpoor performance may be obtained if the true probability density functions are different from those assumed by the model,while AIS are nonlinear models, which make them flexible in modeling real world complex relationships.

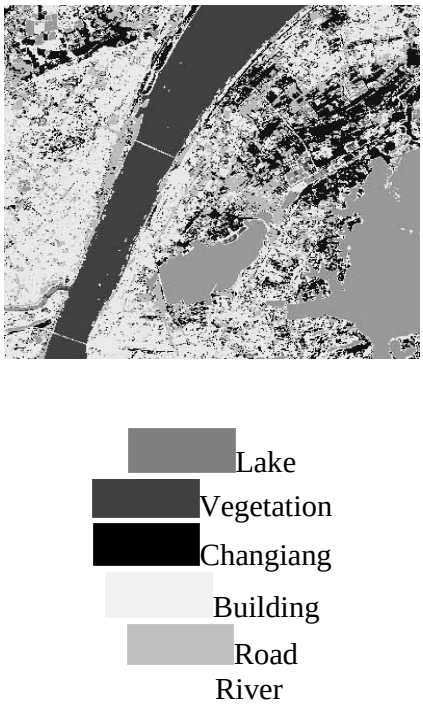

Fig.5 The classification image using Artificial Immune classifier

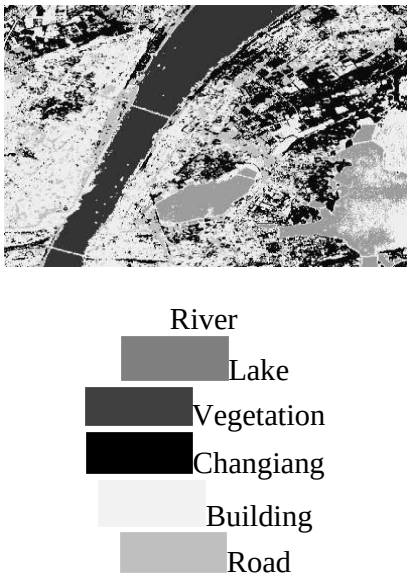

Fig.6 The classification image using maximum likelihood classifier

Table 1 Confusion Matrix(Maximum likelihood method)Table 2 Confusion Matrix (AIS method).

	Reference Data				
	River	Lake	Vegetation	Building	Road
River	100	0	0	0	0
Lake	0	100	21	1	0
Vegetation	0	0	59	13	1
Building	0	0	20	82	15
Road	0	0	0	4	84
Total	100	100	100	100	100
Accuracy	100%	100%	59%	82%	84%
Overall Accuracy	85.0%				
Kappa Coefficient	0.8125				

	Reference Data				
	River	Lake	Vegetation	Building	Road
River	100	0	0	0	0
Lake	0	100	17	1	0
Vegetation	0	0	76	12	1
Building	0	0	7	84	10
Road	0	0	0	3	89
Total	100	100	100	100	100
Accuracy	100%	100%	76%	84%	89%
Overall Accuracy	89.8%				
Kappa Coefficient	0.8725				

5. CONCLUSION

In this paper, we synthesize the advantages of artificial immune system, and proposed a new remote sensing image classification algorithm using Clonal Selection Algorithm which is a basis of the immune system. A quantitative comparison between the conventional maximum likelihood statistical classifier and our algorithm was demonstrated that the maximum likelihood statistical classifier is less capable of discriminating Vegetation classes than AIS classifier. Experimental results show that the proposed classification algorithm has high classification precision. It is a good and efficient classification algorithm andcan be applied to remote sensing image classification.

REFERENCES

[1] D. Dasgupta, 1999. Artificial Immune Systems and Their Application. Berlin, Germany: Springer-verlag.

[2] F. M. Burnet., 1978. Clonal selection and after. In: Bell G I, Perelson A S, Pimbley G H eds. The Immunology, NewYork: Marcel Dekker Inc. pp.63-85.

[3] F. M. Burnet., 1959. The Clonal Selection Theory of Acquired Immunity. Cambridge University Press.

[4] J. E. Hunt, D. E. Cooke., 1996. Learning using an artificial immune system. Journal of Network and Computer Application 19(2): pp.189-212

[5] J. H. Carter., 2000. The immune system as a model for pattern recognition and classification. Journal of the American MedicalInformatics Association, 7(3): pp.28-41.

[6] J. Timmis, M.Neal, and J.Hunt. ,2000. An artificial immune system for data analysis. Biosystem, 55(1/3): pp.143-150.

[7] N. De Castro, F.J. Von zuben, 1999. Artificial Immune Systems: Part I-Basic Theory and Application, Tech. Rep-RTDCA 01/99. Campinas, SP: State

[8] University of Campinas.

BIOGRAPHY

K.ARCHANA[1], R.MONIKA[2], DEPARTMENT OF INFORMATION TECHNOLOGY, from ANJALAI AMMAL MAHALINGAM ENGINEERING COLLEGE, KOVILVENNI