Outdoor Image Classification Using Artificial Immune Recognition System (AIRS) with Performance Evaluation by Fuzzy Resource Allocation Mechanism

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Abstract. AIRS classification algorithm, which has an important place among classification algorithms in the field of Artificial Immune Systems, has showed an effective and intriguing performance on the problems it was applied. In this study, the resource allocation mechanism of AIRS was changed with a new one determined by Fuzzy-Logic rules. This system, named as Fuzzy-AIRS and AIRS were used as classifiers in the classification of outdoor images. The classification of outdoor dataset taken from UCI repository of machine learning databases was done using 10-fold cross validation method. Both versions of AIRS well performed over other systems reported in UCI website for corresponding dataset. Fuzzy-AIRS reached to the classification accuracy of 90.00 % in the applications whereas AIRS obtained 88.20 %. Besides, Fuzzy-AIRS gained one more advantage over AIRS by means of classification time. In the experiments, it was seen that the classification time in Fuzzy-AIRS was reduced by about 67% of AIRS for dataset. Fuzzy-AIRS classifier proved that it can be used as an effective classifier for image classification by reducing classification time as well as obtaining high classification accuracies.

1 Introduction

While a new artificial intelligence field named as Artificial Immune Systems (AIS) was emerging in late 1990s, performances of proposed methods were not so good especially for classification problems. However, AIRS system proposed in 2001 has changed this situation by taking attention among other classifiers with its performance [1].

Image segmentation is the process of dividing a given image into homogenous regions with respect to certain features, which correspond to real objects in the actual scene. The segmentation process is perhaps the most important step in image analysis since its performance directly affects the performance of the subsequent processing steps in image analysis [2].

In this study, resource allocation of AIRS was changed with its equivalent formed with Fuzzy-Logic to increase its classification accuracy. To see effects of this modification, trials were made wtih an image segmentation problem. Both versions of algo-

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rithms were used to classify an outdoor image dataset and they were also compared with other classifiers used for same data set beside of being compared with each other. Fuzzy-AIRS obtained the highest classification accuracy among the classifiers reported in UCI website for related dataset consisting of Outdoor Image taken from UCI database [3]. Fuzzy-AIRS, which proved itself to be used as an effective classifier in image classification field by reaching its goal, has also provided a considerable decrease in the number of resources. In conducted application, Fuzzy-AIRS required less resource than half of required by AIRS and by this way, classification time has reduced by a great rate. The rest of the paper is organized as follows. Section 2 presents Artificial Immune Systems and AIRS (Artificial Immune Recognition System. The results obtained in applications are presented in Section 3 for Image data set. Consequently in Section 4, we conclude the paper with summarization of results by emphasizing the importance of this study.

2 Artificial Immune Systems and AIRS (Artificial Immune Recognition System)

Artificial Immune System (AIS) can be defined as a computational system based upon metaphors of biological immune system [1]. The topics involved in the definition and development of Artificial Immune Systems cover mainly: hybrid structures and algorithms that take into account immune-like mechanisms; computational algorithms based on immunological principles, like distributed processing, clonal selection algorithms, and immune network theory; immune based optimization, learning, self-organization, artificial life, cognitive models, multi-agent systems, design and scheduling, pattern recognition and anomaly detection and lastly immune engineering tools [1], [3].

In unsupervised learning branch of AISs, there are lots of works conducted by researchers Dasgupta, De Castro, Timmis, Watkins, Neal…etc [1], [3], [8]. There are only two studies in supervised AISs. First of these was performed by Carter [8]. The other work is AIRS (Artificial Immune Recognition System), proposed by A.Watkins which is a supervised learning algorithm inspired from the immune system [3].

The used immune metaphors used in AIRS are: antibody-antigen binding, affinity maturation, clonal selection process, resource competition and memory acquisition. AIRS learning algorithm consists of four stages: initialisation, memory cell recognition, resource competition and revision of resulted memory cells.

2.1 AIRS Algorithm

The AIRS algorithm is as follows:

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1. Initialization: Create a random base called the
   memory pool (M) and the pool (P).
2. Antigenic Presentation: for each antigenic pattern
   do:
      a) Clonal Expansion:
      For each element of M determine their affinity to
      the antigenic pattern, which resides in the same
      class. Select highest affinity memory cell (mc)
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and clone mc in the proportion to its antigenic
affinity to add to set of ARBs (P).
b) Affinity Maturation:
Mutation each ARB descendant of this highest
affinity mc. Place each mutated ARB into P.
c) Metadynamics of ARBs:
Process each ARB through the resource allocation
mechanism. This will result in some ARB death,
and ultimately controls the population. Calculate
the average stimulation for each ARB, and check
for termination condition.
d) Clonal Expansion and Affinity Maturation:
Clone and mutate a randomly selected subset of
the ARBs left in P based in proportion to their
stimulation level.
e) Cycle:
While the average stimulation value of each ARB
class group is less than a given stimulation
threshold repeat from step 2.c.
f) Metadynamics of Memory Cells:
Select the highest affinity ARB of the same class
as the antigenic from the last antigenic interac-
tion. If the affinity of this ARB with the anti-
genic pattern is better than that of the previ-
ously identified best memory cell mc then add the
candidate (mc-candidate) to memory set M.
Additionally,if the affinity of mc and mc-
candidate below the affinity threshold, then re-
move mc from M.
3. Cycle. Repeat step 2 until all antigenic patterns
have been presented.
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2.2 Fuzzy Resource Allocation Method

The competition of resources in AIRS allows high-affinity ARBs to improve. According to this resource allocation mechanism, half of resources are allocated to the ARBs in the class of Antigen while the remaining half is distributed to the other classes. The distribution of resources is done according to a number that is found by multiplying stimulation rate with clonal rate. In the study of Baurav Marwah and Lois Boggess, a different resource allocation mechanism was tried [5]. In their mechanism, the Ag classes occurring more frequently get more resources. Both in classical AIRS and the study of Marwah and Boggess, resource allocation is done linearly with affinities. This linearity requires excess resource usage in the system that results long classification time and high number of memory cells.

In this study, to get rid of this problem, resource allocation mechanism was done with fuzzy logic. So there existed a non-linearity because of fuzzy rules. The difference in resource number between high-affinity ARBs and low-affinity ARBs is bigger in this method than in classical approach.

The input variable of Fuzzy resource allocation mechanism is stimulation level of ARB hence the output variable is the number of resources that will be allocated to that ARB. As for the other fuzzy-systems, input membership functions as well as output membership functions were formed. The input membership functions are shown in Fig. 1.

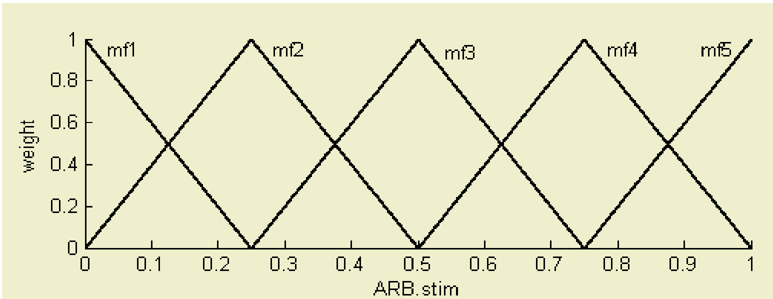

Fig. 1. Input membership functions

The input variable, ARB.stim, varies between 0 and 1. A membership value is calculated according to this value using input membership functions. In this calculation, two points are get which are the cutting points of membership triangles by the input value, ARB.stim. Also these points are named as membership values of input variable for related membership function. The minimum of these points is taken as the membership value of input variable x, ARB.stim (Eq. (1)).

$$\mu_{A\cap B}(x) = \min(\mu_A(x), \mu_B(x)),\ x\in X. \tag{1}$$

Here in Eq. (1), $\mu_A(x)$ is the membership value of x in A and $\mu_B(x)$ is the membership value of x in B, where A and B are the fuzzy sets in universe X. The calculated input membership value is used to get the output value through output membership functions that are shown in Fig. 2.

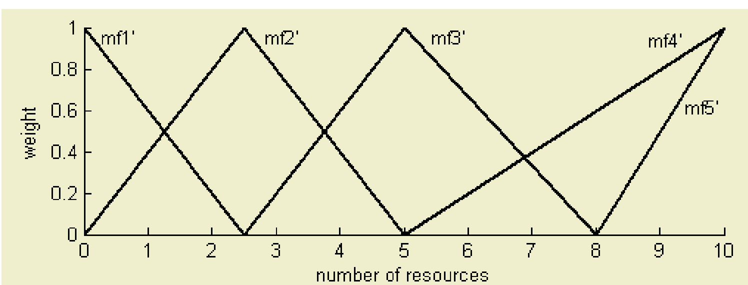

Fig. 2. Output membership functions

In the x-axis of this Figure, allocated resource number that will be calculated using the membership functions for the ARB is shown which changes between 0-10. The weight in the y-axis that is the input membership value get as explained above intersects the membership triangles at several points.

Here mf1, mf2…etc are the labels of input membership triangles and mf1’, mf2’…etc are the labels of output membership values. The rules in Table 1 define which points will be taken to average. For example if the input value cuts the triangles mf1 and mf2 among the input membership functions, then the points to be averaged will be only the ones of mf1’ and mf2’ triangles in the output membership functions.

These linguistic values were determined in such a manner that the allocated resource number for ARBs which have stimulation values between 0 and 0.50 will be less while for ARBs which have stimulation values between 0.50 and 1 will be more.

2.3 Measures for Performance Evaluation in AIRS

In this study, the classification accuracies for the datasets were measured according to the Eq. (2). [1]:

$$accuracy(T) = \frac{\sum_{i=1}^{|T|} assess(t_i)}{|T|}, t_i \in T \; . \tag{2}$$

$$assess(t) = \begin{cases} 1 & if \quad classify(t) \equiv t.c \\ 0 & otherwise \end{cases} \; . \tag{3}$$

In equation 3, T is the set of data items to be classified (the test set), $t\epsilon T$, $t.c$ is the class of the item t, and classify (t) returns the classification of t by AIRS.

For test results to be more valuable, k-fold cross validation is used among the researchers. It minimizes the bias associated with the random sampling of the training [5]. In this method, whole data is randomly divided to k mutually exclusive and approximately equal size subsets. The classification algorithm trained and tested k times. In each case, one of the data subsets is taken as test data and the remaining folds are added to form training data. Thus k different test results exist for each training-test configuration. The average of these results gives the test accuracy of the algorithm [5]. We used this method as 10-fold cross validation in our applications. But we also conducted our experiments in such a way that there runs, one for each of the possible configurations of the traing versus test data set. The average of these three test results gave us the test result for each fold. So we obtained 30 results in total to average.

3 Fuzzy-AIRS Performance Analysis

The classification performance of Fuzzy-AIRS was analyzed in outdoor image data set.

3.1 Outdoor Image Data Set

The problem to be solved here is classification of outdoor image dataset. This dataset was taken from Vision Group, University of Massachusetts in 1990 with the contributions of Carla Brodley. In image segmentation data set, the instances were drawn randomly from a database of 7 outdoor images. The images were hand segmented to create a classification for every pixel. Each instance is a 3x3 region. In training data there are 210 instances and in test data there are 2100 instances with 19 continuous attributes [2, 3].

In the data set, the third attribute is the same for all inputs therefore while the simulations are being done this attribute is not added to network. The existing seven classes are grass, path, window, cement, foliage, sky, and brickface [2, 3].

Fuzzy-resource allocation mechanism provided Fuzzy-AIRS to classify Outdoor Image data set with 90.00% classification accuracy. The accuracy reached with the use of AIRS was 88.2%.

The results obtained by Fuzzy-AIRS and AIRS for Outdoor Image dataset is presented in Table 1. The values of used resource number and classification time in the table are recorded for the highest classification accuracy.

Table 1. Obtained results by Fuzzy-AIRS and AIRS for Outdoor Image Dataset

Outdoor Image dataset	**Classification accuracy (%)**	**Number of resources used in classification algorithm**	**Classification Time (Sec)**
AIRS	88.20	700	180
FuzzyAIRS	90.00	400	60

The classification accuracy otained by Fuzzy-AIRS for Outdoor Image dataset is the highest one among the classifiers reported in UCI web site. The comparison of Fuzzy-AIRS with these classifiers with respect to the classification accuracy is shown in Table 2.

Table 2. Fuzzy-AIRS's classification accuracy for Outdoor Image dataset problem with classification accuracies obtained by other methods in UCI web site

Author(Year)	**Method**	**Classification Accuracy (%)**
Tin and Kwork (1999)	SVM	83.00
Lim et.al. (2000)	Decision Trees	85.01
Tolson (2001)	k-NN	85.2
Çoşkun and Yildirim (2003)	PNN	87.6
Çoşkun and Yildirim (2003)	GRNN	86.7
Our study (2005)	**AIRS**	**88.2**
Our study (2005)	**Fuzzy-AIRS**	**90.00**

The considerable difference between the accuracies of Fuzzy-AIRS and the classifier that reached highest accuracy previously can be seen easily from the table. We don't include AIRS for this comparison because we want to emphasize the classification power of Fuzzy-AIRS over the other classifiers in the table.

4 Conclusions

In this study, the resource allocation mechanism of AIRS that is among the most important classification systems of Artificial Immune Systems was changed with a new one that was formed using fuzzy-logic rules.

In the application phase of this study, Outdoor image dataset data set was used. In the classification of this dataset, the analyses were conducted both for the comparison of reached classification accuracy with other classifiers in UCI web site and to see the effects of the new resource allocation mechanism.

According to the application results, Fuzzy-AIRS showed a considerably high performance with regard to the classification accuracy for Outdoor image dataset. The reached classification accuracy of Fuzzy-AIRS for Outdoor image dataset was 90.00% which was the highest one among the classifiers reported in UCI web site. With this result, it is going clearer that AIRS is ready for real world problems with some improvements possibly done.

Beside of this success, Fuzzy-AIRS reduced the classification time with respect to AIRS approximately by the amount of 66.7% for Outdoor image dataset. This was the result of decrease in resource number done by fuzzy-resource allocation. If we consider the importance of classification time for image data and large data sets, this improvement makes AIRS more applicable. An increase in classification accuracy was also obtained by Fuzzy resource allocation over the AIRS that is 1.8%.

References

1. Watkins, A. *AIRS: A Resource Limited Artificial Immune Classifier*. Master Thesis, Mississippi State University, Mississippi, (2001).
2. Coşkun N., Yıldırım T., Image Segmentation Using Statistical Neural Networks. In *Proceedings of International Conference On Artificial Neural Networks / International Conference on Neural Information Processing (ICANN/ICONIP)*(Istanbul, Turkey, June 26-29,2003). 154-156.
3. ftp://ftp.ics.uci.edu/pub/machine-learning-databases
4. Marwah, G. and Boggess, L. Artificial immune systems for classification: Some issues. In *Proc. First Intl. Conf. Art. ImmuneSystems* (University of Kent at Canterbury, England, Sep. 2002) 149-153.
5. Tin, J. and Kwork, Y. Moderating the Outputs of Support Vector Machine Classifiers. *IEEE Trans. On NN 10,* 5 (1999),1018-1031.
6. Tolson, E. *Machine Learning in the Area of Image Analysis and Pattern Recognition*, Advanced Undergraduate Project Spring 2001.
7. Loh, W., Tim, L. and Shih, Y. A Comparison of Prediction Accuracy, Complexity, and Training Time of Thirty-Three Old and New Classification Algorithms. *Machine Learning 40,* 3 (2002),203-228.
8. De Castro, L.N and Timmis, J., Artificial Immune Systems: A New Computational Intelligence Approach, Springer-Verlag Press (2002)