

Texture Image Segmentation Method Based on Artificial Immune and Maxim Entropy

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Abstract:

This paper presents a hybrid technique for the classification of the magnetic resonance images (MRI). The first part of this paper mainly introduces the principle of the Artificial Immune System (AIS) and the immune algorithms based on upon. A new immune algorithm was proposed based on image segmentation algorithm of maxim entropy method. This result shows that the proposed technique is robust and effective compared with other recent work.

Keywords: artificial immune system, maxim entropy, image segmentation.

1. Introduction

The study of this immune system could propagate a new terrain of study based on abundant theories to generate resources for computer-based solutions. This growing field has is called the Artificial Immune System (AIS), and it utilizes notions from immunology to help build appropriate models which can perform tasks in engineering applications. The human immune system is a complex natural defense mechanism [1]. The artificial immune system aims to extract the unique information processing mechanism of biological immune system, research and design corresponding models and algorithms, and then apply it to solve a variety of complex problems. The immune system's unique self-learning, self-organization and high degree of parallelism, provide a powerful information processing and problem solving paradigm, provides a new way for people to solve hot and difficult problems in many engineering field. This remarkable information processing biological system has caught the attention of computer science in recent years. One of the important tasks in data mining is classification [2]. The more complex problems need to be solved, the greater the advantages of immune programming, and the complexity and the great computation of the image segmentation itself, so that the advantages of immune programming can be fully exploited. Therefore, the application of the immune algorithm in image segmentation can achieve more accurate segmentation results. Cong Lin [3] proposed a novel algorithm based on immune clone selection and optimal entropy theory. Immune clone selection algorithm performs not only local but also global search, and has better performance than Genetic Algorithm (GA) in searching for the optimal entropy threshold of images. Huang [4] proposed a method based on the combination of the artificial immune network and the support vector domain description (SVDD) for the unsupervised image segmentation. Liu YunLong [5] proposed a method based on artificial immune algorithm and fuzzy clustering algorithm. Artificial immune algorithm is utilized for optimizing fuzzy clustering image segment, which has excellent ability on exploration and exploitation [6]. Simulation results show that proposed algorithm can automatically segment image with high validity.

Accurate brain tissue segmentation from magnetic resonance (MR) images is an essential step in quantitative brain image analysis. It is the most important clinical value of MRI image is reflected in detecting internal tissue's lesions, variability and soft tissue's damage by MRI scanning to obtain patient's information [7]. Magnetic Resonance Imaging (MRIs) is currently the best medical imaging tools that permit cross-sectional views of the human body with excellent tissue contrasts. Al-Badarneh [8] et al. proposed an automated classification model to be utilized for MRI image tumor classifications. The results of this classification depicted how NNs as well as KNN models affect tumor classifications.

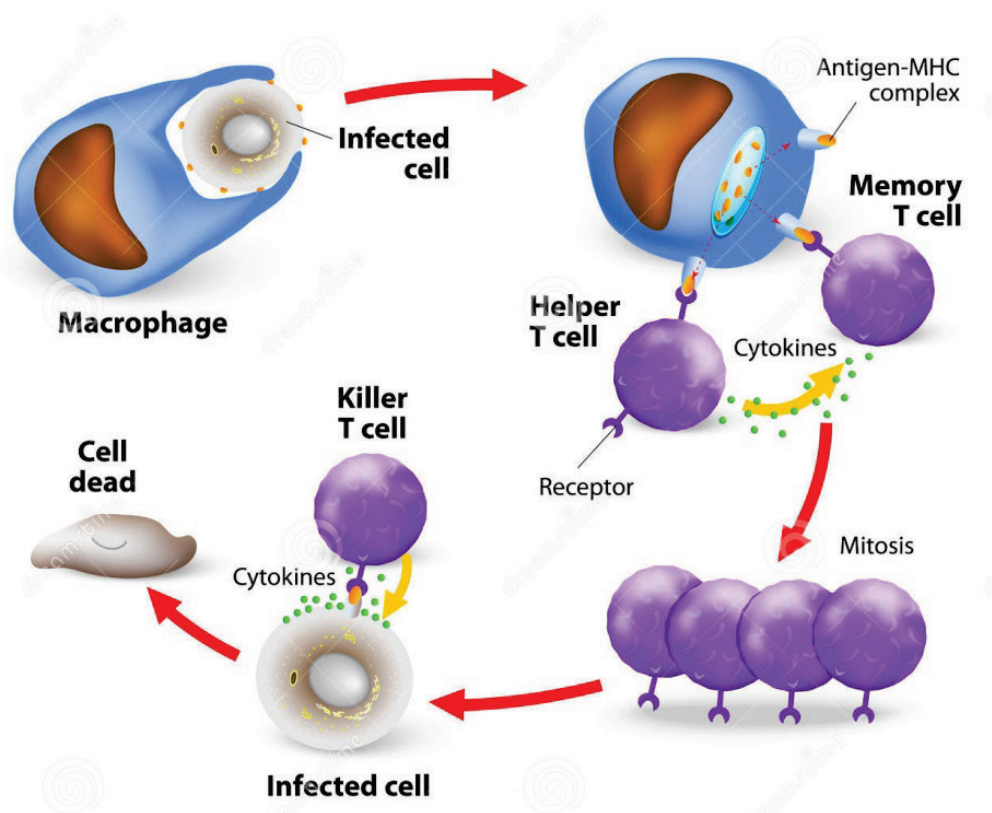


Fig. 1. Pictorial representation of the essence of cell-mediated immune response.

2. Methods

2.1 Principles of immune system

The role of the immune system can be simply described as immune cell antigen recognition, corresponding immune cells are activated and produce clonal selection and cell hyper mutation reaction, finally produce the corresponding antibody antigen phagocytosis and destroy. The main function of this is the immune cell, whose main function is to identify various cell protoplasm, distinguish between the "self" and "I". The self refers to the tissue cell of the organism itself, and the non self refers to the external invasion of the harmful pathogen that is distinct from its own tissue cells. Immune cells refer to the cells involved in the immune response, including phagocytes, NK cells, lymphocytes, etc. the cells of the immune system, in general, mainly refer to lymphocytes. Two of the most important-cells in this process are white blood cells, called T-cells, and B-cells. Any substance that is capable of generating such a response from the lymphocytes is called an antigen or immunogen. B-cells are responsible for the production and secretion of antibodies, which are specific proteins that bind to the antigen. Each B-cell

can only produce one particular antibody. B cells are also affected by Helper T cells during the immune response. The helper cells, which are type of T cells, are essential to the activation of B-cells. When the antigen invades the body, antibody and antigen secreted by B cells will bind. And when the binding force between them exceeds a certain limit, B cells will secrete this antibody the occurrence of clonal expansion, resulting in a large number of identical and similar. After cloning and amplification, a part of B cells are cloned and differentiated into memory cells, which can be activated rapidly after the same antigen, so as to realize the immunological memory of antigen. The clonal expansion of B cells is regulated by T cells, and when B concentration is increased to a certain extent, T cells inhibit B cells, thereby preventing the unlimited replication of B cells. In the real immune system, pathogens produce antigens when invading a host [9]. It is these antigens that are matched with the antibodies of the immune system. A more contentious theory is the immune network theory first proposed by Jerne and reviewed by Perelson. This theory proposes that a network dynamically maintains the immune memory using feedback mechanisms. The function principle of immune system is shown in Fig. 1.

The immune Network theory had been proposed in the mid-seventies. The hypothesis was that the immune system maintains an idiotic network of interconnected B cells for antigen recognition. These cells both stimulate and suppress each other in certain ways that lead to the stabilization of the network. Two B cells are connected if the affinities they share exceed a certain threshold, and the strength of the connection is directly proportional to the affinity they share.

2.2 Clonal selection principle

The clonal selection principle [10] describes the basic features of an immune response to an antigenic stimulus. It establishes the idea that only those cells that recognize the antigen proliferate, thus being selected against those that do not. The main features of the clonal selection theory are that:

- (1) The new cells are copies of their parents (clone) subjected to a mutation mechanism with high rates (somatic hyper mutation);
- (2) Elimination of newly differentiated lymphocytes carrying self-reactive receptors;
- (3) Proliferation and differentiation on contact of mature cells with antigens.

2.3 The principle of maximum entropy image segmentation algorithm based on artificial immune

Combining information entropy and immune bionics principle, genetic algorithm is selected as search algorithm. The clonal selection algorithm is applied to the evolutionary selection process of antibodies. The concentration of the population and the expected reproduction rate of the individual are used as the criteria for judging the individual's merits. In this paper, antigen represents objective function, and antibody represents the optimal solution of objective function. Information entropy is selected as metric parameter.

Each antibody consists of M bit letters, and the number of antibodies is N . The number of the alternative letters for each antibody is L : k_1, k_2, \dots, k_j . Then the information entropy of N antibodies is defined as following:

$$H(N) = \frac{1}{S} \sum_{j=1}^S H_j(N) \quad (1)$$

Where: $H_j(N) = \sum_{i=1}^I -p_{ij} \log p_{ij}$, $H_j(N)$ is j 'th information entropy of N 'th antibody, P_{ij} is the

j 'th probability of N 'th antibody.

- Affinity maturation is a very complex biological process which enables activated B-cells to produce antibodies with increased affinity for a given antigen. Affinity of antibodies represents the similarity degree of two antibodies. The similarity degree of antibody X and antibody Y is defined below:

$$ass_{xy} = \frac{1}{1 + H(2)} \quad (2)$$

- Affinity of antigen to antibody represents the degree of recognition of antigens by antibodies. The affinity of antibody v and antigen v is defined as follows:

$$aff_v = opt_v \quad (3)$$

Where, opt_v is the binding degree of antigen and antibody, and is usually expressed by the fitness function between antigen and antibody.

The basic steps of the algorithm are as follows:

(1) The initial antigen population is generated, N individuals are randomly generated, and N_{get} individuals are extracted from the memory bank to form the initial population.

(2) Expected reproductive rate of individuals e_v is selected as the evaluation criterion of population, which is defined as follows:

$$e_v = \frac{aff_v}{c_v} \quad (4)$$

Where, Individual concentration

$$c_v = \frac{1}{N} \sum_{y=1}^N ac_{xy} \quad (5)$$

$$ac_{xy} = \begin{cases} 1 & ass_{xy} \geq T \\ 0 & ass_{xy} < T \end{cases} \quad \text{which, } T \text{ is Individual fitness threshold.}$$

(3) Arrange the initial population in descending order of e_v , and select the first N individuals as the first population. Then the first N_{get} individuals are added to the memory bank.

(4) Determines whether the end condition is satisfied (whether the algebra is already larger than the prescribed algebra), until stopping criteria are met.

(5) Emergence of new populations. For the calculation results (4), the selection, crossover and mutation of the antibody population were carried out, and a new generation of population was obtained. Then, the individuals with memory were extracted from the memory bank to form a new generation

(6) Carry out (2). And the algorithm flow is shown as follows:

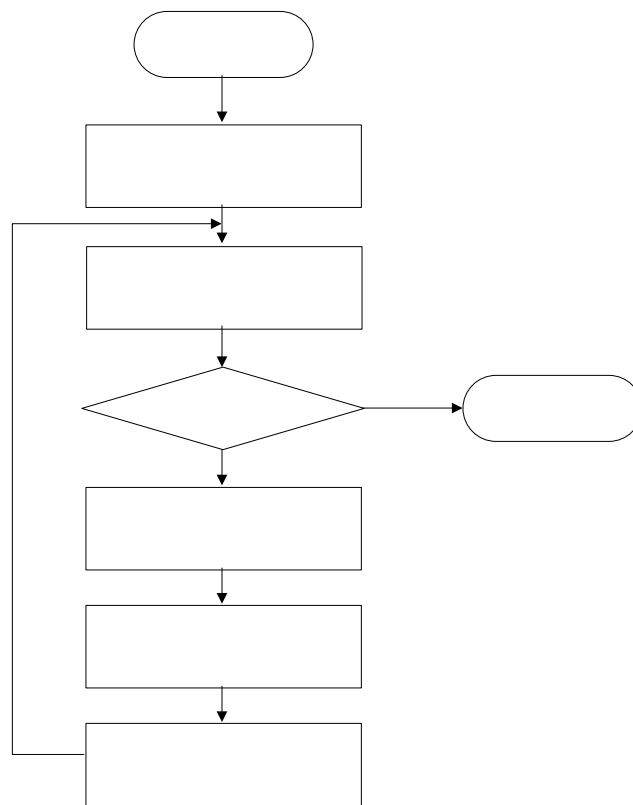


Fig. 2 Algorithm flow of immune reaction

3 Results and discussions

3.1 Segmentation effect comparison of immune algorithm and OSTU

The ultimate purpose of this paper is to realize the efficient segmentation of medical images by the method of hybrid algorithm. Because the texture feature of medical image is relatively complex. So this experiment uses the simple texture image for segmentation, after a successful test can be used for brain medical image processing.

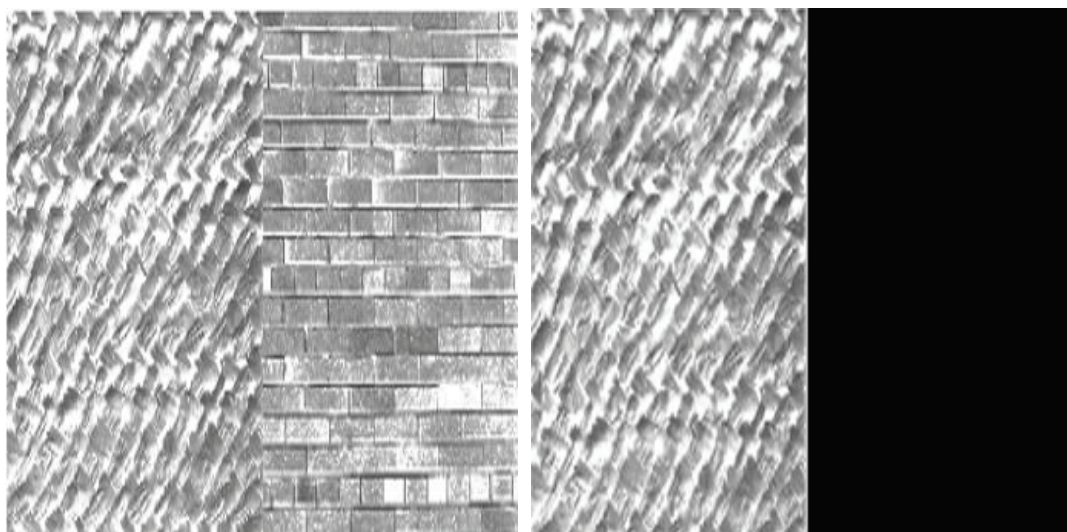


Fig.3. Example image segmentation results

In this paper, the antigen is the maximum entropy of the image $\phi(s, t)$; which, s, t are antibodies, respectively. Memory library is initialized: where, G is the number of generations, N_{get} is the number of antigens which is stored in the memory bank and from the memory bank. T is individual affinity preset threshold of antigen, the number of preset threshold $N=100$, Mutation probability P_m is 0.01. The results are as follows:

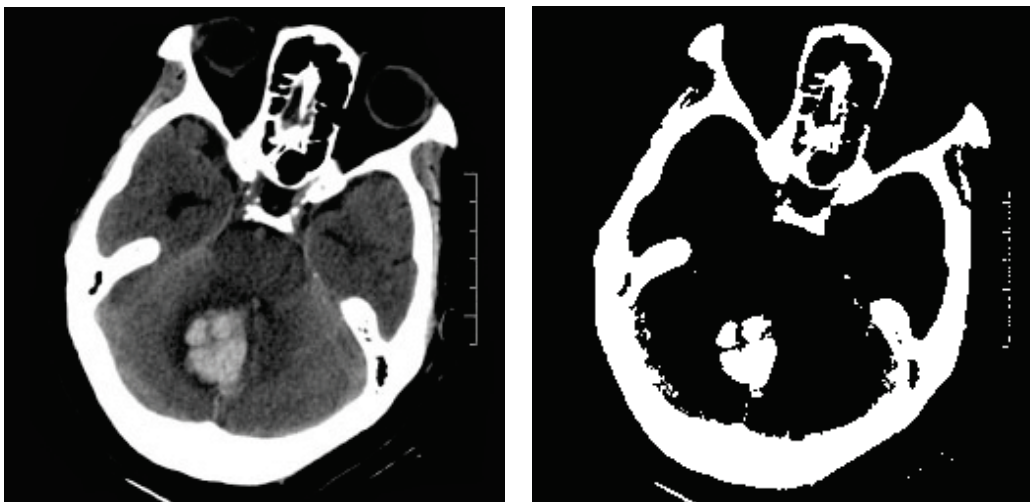


(a) Original MRI image of head (b) Segmented image using this method (c) Ostu automatic segmentation

Fig. 4 Immune maximum entropy segmentation results ($G=51, N_{get}=10, T=0.8$)

The results showed that, the optimal threshold obtained by the method we proposed is $(95,93)$, and the threshold of OSTU is 40. In Fig. 4 by maximum entropy method using a two-dimensional double threshold method can locate the edge of brain is very accurate for extraction, for subsequent image analysis processing is of great significance, and Fig. 4(c) automatic threshold segmentation belongs to the single threshold segmentation method, it can only put the gray image is divided into two parts to so in the segmentation, segmentation results will lose some useful information.

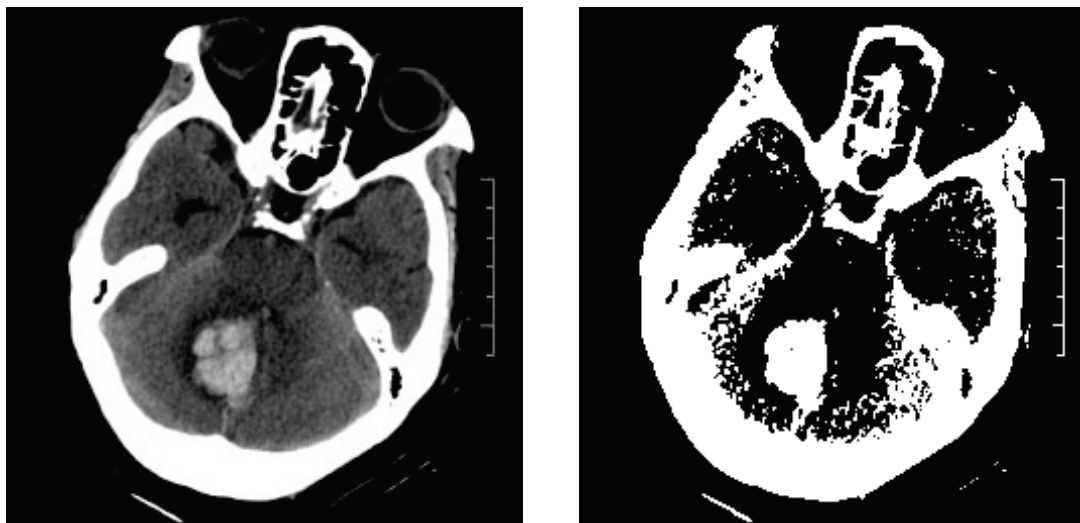
Automatic threshold segmentation results show that the segmentation effect is not ideal, and there are many burrs on the edge, which brings a lot of inconvenience to the subsequent analysis and processing of images.



(a) Original image

(b) segmented image

Fig. 5 Immune maximum entropy segmentation results ($G=100, N_{get}=20, T=0.95$)



(a) Original image

(b) segmented image

Fig. 6 Automatic threshold segmentation results

At each iteration of the film recommendation Artificial Immune Systems the concentration of the antibodies is changed according to the formula given on the next page. This will increase the concentration of antibodies that are similar to the antigen and can allow either the stimulation, suppression, or both, of antibody-antibody interactions to have an effect on the antibody concentration.

From the experimental results, we can see that the higher the algebra is, the closer the antibody is to the optimal solution. The result is also affected by the number of memory stocks, because evolution is converging in the best direction accompanied by improvement of number of memory stocks. Judgment of individual affinity also affects antibodies, because the evolutionary trend depends greatly on the affinity of the antigen for clonal selection. Besides, Initial population size has a great impact on the algorithm, and is mainly used for convergence performance.

4. Discussions

It can be seen from figure 4 and figure 6 that the two-dimensional maximum entropy image segmentation using immune algorithm is better than the automatic threshold segmentation. But in this experiment, two problems should be paid attention to in double threshold segmentation. The first is the selection of algebraic G . From the experiment results, the maximum entropy function of the double threshold calculation is relatively large, so G don't get too large, and the experiments show that under general conditions, $G = 300$ and $G > = 50$ in other same conditions for most of the image results and there is no great difference. Therefore, for two-dimensional maximum entropy threshold segmentation, algebraic G can be done at about 50. Of course, the higher the immune evolution algebra is, the more complete and advanced the evolution is, and the closer the solution is to the actual solution. In addition, after changing the value of T , the experimental results show that the larger the value of T , the more stringent the choice of antigen evolution, and thus the results are closer to the optimal solution.

The image segmentation experiments that improved clonal selection algorithm combining respectively with 2-D maximum entropy image segmentation method show that improved algorithm better than the basic one.

References

- [1] Jon Timmis a, Mark Neal a, John Hunt. An artificial immune system for data analysis. *BioSystems*, 2000(55): 143–150
- [2] Freitas A, Timmis J (2003) Revisiting the foundations of artificial immune systems: a problem oriented perspective. In: LNCS 2787, Springer, pp 229-241.
- [3] Cong Lin, Sha Yu-Heng, Jiao Li-cheng. Application of Immune Clone Selection Algorithm to Image Segmentation. *Journal of Electronics & Information Technology*, 2006, 28(7): 1169-1173.
- [4] Huang W L, Jiao L C. Artificial immune kernel lustering network for unsupervised image segmentation. *Progress in Natural Science*, 2008, 18(4): 455-461.
- [5] Liu Yunlong, Lin Baojun. Fuzzy clustering image segmentation algorithm with high validity optimized by artificial immune algorithm. *Control and Decision*, 2010, 25(11): 1679-1683.
- [6] J Ji, J Liu, P Liang, A Zhang. Learning Effective Connectivity Network Structure from fMRI Data Based on Artificial Immune Algorithm. *PloS one*, 2016, 11 (4):1-32.
- [7] Tan Guangxing. Application and Research of Immune Clustering Algorithm in MRI Brain Image Segmentation. Liuzhou: Guangxi University of Science and Technology, 2015.
- [8] Al-Badarneh A, Najadat H, Alraziqi AM. A classifier to detect tumor disease in MRI brain images. In *Advances in Social Networks Analysis and Mining (ASONAM)*, 2012 IEEE/ACM International Conference on IEEE. 784-787.
- [9] Xinglong JiangYang, YuLulu, ZhaoHuijie Liu. Constrained nondominated neighbor immune multiobjective optimization algorithm for multimedia delivery. *Multimedia Tools and Applications*, 2017, 76 (16): 17297-17317.
- [10] Rui Li, Weida Zhan, Ziqiang Hao. Artificial Immune Particle Swarm Optimization Algorithm Based on Clonal Selection. *Boletín Técnico*, 2017, 55(1):158-164.