Artificial Immune Systems and Aerial Image Segmentation

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ABSTRACT

This paper describes our initial investigations in applying artificial immune systems to feature segmentation in remotely sensed images. The current generation of commercial imaging satellites provides increased opportunities for automated image analysis due to the large volume of high resolution imagery they will produce. Artificial immune systems (AIS) are successful in other pattern recognition tasks and have several similarities to the aerial image classification problem. We use an AIS for road pixel identification and observe several areas for further development.

INTRODUCTION

In this introduction, we examine the functions of a natural immune system and review the use of AIS for pattern recognition.

The natural vertebrate immune system has two systems of protection. The first is a general response directed at any pathogens. The second is an adaptive immune response developed against a specific invader and which provides a faster memory response if it reappears. Characteristic antigen proteins cover the surfaces of viruses and cells. The immune system uses antigens as a biological fingerprint to separate self and nonself. Each cell belonging to an individual's body has a unique set of antigen proteins called a major histocompatibility complex. Biological materials without this complex do not belong to the body and can be flagged for deletion. Several kinds of cells implement the actual operations of detecting intruders, marking them as foreign, removing or destroying them, and retaining a memory to provide a faster response in the future. These cells derive from blood cells and patrol the body by traveling the blood and lymphatic system.

The bone marrow produces stem cells that mature into two types of lymphocytes: B (bone) cells and T (thyroid) cells. The B cells originate in the bone marrow and enter the lymphatic system. The function of a B cell is to detect foreign antigens and assemble antibody proteins marking the antigen for deletion by other immune system products. A B cell excited by antigens will, with the aid of a helper T cell, transform into a blast cell and rapidly begin producing copies of itself. Some of these cells will transform into plasma cells that also produce antibodies specific to the triggering antigen. Others will become memory cells that are a more sensitive to the triggering antigen than the original B cell.

In the thymus, T cells mature into two classes: helper and killer. The helper T cells aid the growth of B and T cells and produce a variety of proteins useful in the immune system. The killer T cells attack cells of the body that become infected. The antigens of a sick cell are typically different from a healthy one, so the T cells can recognize and eliminate the infected cell.

A simplified model of the immune system could consist of a population of detectors, sources of novel new detectors, and a means of screening these new detectors so that only nonself responding ones persist in the population (Negative Selection). The Network Theory attempts to explain how a network of interacting detectors can provide self-nonself discrimination and maintain a long term memory of detectors and limit population size. This theory is the basis for many simulations of the natural immune system. We base our work on Negative Selection to simplify these initial experiments.

Previous work has produced results on a variety of pattern recognition problems and theoretical aspects of AIS. For a survey including applications to computer security, see [1]. These papers generally belong to Network Theory or Negative Selection implementations. [2] attempted to use a network immune system as an associative memory for the recognition of 64x64 pixel binary images. To start with, the detector population is exposed to the image. Detectors responding to the image increase in concentration and form self-sustaining

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networks with complementary detectors. Then, when the system sees a similar image, the most successful detector from the first exposure should give the strongest response. The main difficulty with their approach seemed to be ensuring that a memory state would be stable.

However, [3] present a different network AIS that functions on test data and learns a DNA sequence recognition problem with 90% accuracy. Theoretical modeling has shown the network theory to be a possible explanation for various characteristics of the natural immune system, and it is computationally similar to neural networks and genetic algorithms [4,5]. Possibly these varying results are implementation dependent, just as neural network and GA performance can vary according to the exact algorithms used. These results prompted us to consider an AIS algorithm with less complicated dynamics, Negative Selection.

In [6], AIS using Negative Selection detected tool breakage in simulated time series of cutting force for machine tools. The cutting force varies periodically as teeth of the cutter move into and out of the workpiece. The same system can detect when a periodic signal contains a small amount of noise. The AIS performed satisfactorily in both applications. AIS are also applicable to computer security systems protecting against viruses and warning of unusual usage patterns.

A genetic algorithm form of artificial immune system is shown in [7,8] to optimize a detector population for multiple fitness peaks.

In summary, AIS, like genetic algorithms and neural nets, is a tool for adaptive pattern recognition. By fitting a detector population to the problem, rather than trying for a single optimum detector, they allow for flexible coverage of feature space and the fitting of multiple local optima. Even though the relative merits of different AIS implementations is still an open question, they have proved useful for pattern classification in several applications. Our investigations concern the use of AIS in feature extraction / segmentation of aerial or high resolution satellite images.

AERIAL IMAGE SEGMENTATION

Our investigation into aerial image segmentation concentrates on the extraction of road pixels from single band IR-sensitive aerial imagery. We used aerial data as a model for high resolution satellite imagery available in the near future. Road extraction is a problem of long-term interest for the remote sensing community. In flight simulation, vector road data allows simulation of road appearances in non-visual sensor modalities. Extracting roads would likely be the first step in wide area satellite traffic studies. Tasks requiring updating or extending existing GIS systems could also benefit. Another potential application of AIS is target screening of unmanned aerial vehicle imagery. An AIS could be trained with a particular patrol area as self. Any vehicles or other features moving into the area that were not originally present would register as non-self and be brought to an analyst's attention.

Previous work on this problem has incorporated expert systems, model-fitting, and neural networks, however evolving populations of detectors are relatively unexplored. Yet, the ability to easily incorporate new information is a critical requirement of an aerial image processing system operating on different parts of the world with diverse types of architecture, terrain and vegetation. A fundamental difference between the AIS and other pattern recognition paradigms is that its goal is to find many detectors that do not respond to the desired class. Most other systems and GAs attempt to find a single detector or classification scheme that only responds to the target class. Is it easier to find a single optimum detector for the desired region of feature space or a population of detectors that weed out all non-target areas? The following motivating example suggests the population of non-self detectors is easier to find since there are more possible paths leading to a solution.

Assume a discrete feature space represented by an M-digit bit string. Let T=0.....010.....0 where one indicates the region of feature space for the target pattern. The one is at the kth position of 0....M-1. Let us consider two ways to produce detectors for this bit string. Assume 1 and 0 are equally likely.

Method A: Random Search. Generate random binary numbers until one exactly matching T is found. Evaluate test strings by counting the number of non-matching bits. If all bits match, then it belongs to the target class.

Method B: Immunological Method. Generate random binary numbers, if position k is 0, add the number to the population. When the logical OR of the population equals the complement of T, stop. If none of the population have any bits in common with the test string, then it belongs to the target class.

The probability that none of N trials of method A will yield the correct answer is:

$$\begin{aligned} P_A &= P_{not\ correct\ in\ N\ trials} \\ &= (1-P_{correct\ in\ trial})^N \\ &= (1-\frac{1}{2^M})^N \end{aligned}$$

In method B, we want to generate a set of binary strings whose logical OR is all ones, except for the kth digit. For each N trials, the number of strings with 0 in the kth digit is given by the binomial distribution with p=q=1/2. The probability of not finding the correct population in N trials is P_B, which is 1 minus the probability of generating the desired population, P_d. For N trials, we have $P_{Binomial}$ the probability of getting i strings with the kth digit zero. $P_{fills space}$ is the probability that the detector population fills all of feature space except the target region. For space to be filled, each binary digit must have a 1 value in at least one of the i trials. Only M-1 digits are of concern here, since the value of the kth digit is 0 for these i trials.

$$P_B = 1 - P_d$$

$$P_{Binomial}(N, i, p, q) = \frac{N!}{(N-i)!i!}(p)^N (q)^{N-i}$$

$$P_{fills space}(i, M) = (P_{at\ least\ one\ of\ i\ trials\ for\ a\ digit=1})^{M-1}$$

$$P_B = 1 - \sum_{i=0}^{N} P_{Binomial}(N, i, 1/2, 1/2)\, P_{fills space}(i, M)$$

$$P_B = 1 - \sum_{i=0}^{N} \frac{N!}{(N-i)!i!}\left(\frac{1}{2}\right)^N (1-\frac{1}{2^i})^{M-1}$$

Figure 1 shows the probability of no solution for values of M and N in the random search case. Figure 2 shows the immunological model. The significance of these graphs is the immunological case converges enormously faster than random search, and the number of trials to generate a population covering all non-self regions is almost independent of M.

This simple model indicates finding a population of detectors that covers non-self feature space may be an easier task than finding a single optimal detector since there are many more ways to arrive at an acceptable solution.

ARTIFICIAL IMMUNE SYSTEM

The goal of these initial experiments is to investigate the feasibility of using an AIS for aerial image segmentation. We attempt to find road pixels using an AIS algorithm performing the following steps:

1. Generate random detectors.
2. Apply these new detectors to the sample data.
3. Delete any detectors misclassifying the sample data.
4. Apply remaining detectors to the test image. Note pixels where a new detector responds better than any previous detector.
5. If enough pixels found improved detectors, go to 1.
6. Output classified image and statistics.

In this case, the detectors were Euclidean hyperspheres composed of an n^2 vector of pixel values plus a radius. This is an n by n square area on the image. If the sum of squared differences response between the image and the detector pixels is less than the radius^2, then the detector is active.

The main idea of this algorithm is only detectors that do not turn on for any of the sample cases join the population. Eventually, enough randomly generated detectors meeting this criterion will accumulate to cover all the non-self regions of feature space. Only the self pixels similar to the sample cases will have an activated detector attached to them in the output image. The 5x5 experiment took 15 minutes on a Pentium Pro Linux workstation.

RESULTS

Our results consist of Fig 3, the original image, Fig 4. hand-classified sample data used to screen detectors and Fig. 5-8 the classified images for 3x3, 5x5, 7x7, 9x9 detectors. The original image was black-filled to exclude labeling, fiducial marks, and borders. The limited amount of sample data included a few road lengths at several orientations. Output images show blurring with the wider detectors, but many of the road pixels are present with some misclassified regions. Overall 10% of the random detectors tried were successful in not responding to the sample data. A more intelligent algorithm to generate trial detectors with a higher success rate could improve computational efficiency. [9] investigates this problem. These results suggest the potential usefulness of AIS in aerial image segmentation, but also show the need to exploit the global geometry of the feature to yield smooth, connected, vectorizable output.

In contrast to our previous work with Genetic Programming [10], AIS do not have the problem of a single detector taking over the population and becoming an evolutionary dead end. The GP also suffered from an interpreted programming language and a tree data structure leading to a non-sequential memory access pattern and poor processor cache management. The AIS using simple kernel detectors can access memory efficiently. Both algorithms are suitable for parallel processing. We would also expect the AIS to adapt to changes in its sample data more readily. All it would need to do is run the existing population on the modified sample data and remove any detectors responding to it. Rerun all remaining detectors on the image. Continue trying new detectors as usual. The GP would need to restart entirely from a random population, if the uncorrelatedness of its fitness landscape prevented its highly optimized detector from evolving to suit the altered conditions.

DIRECTIONS FOR FUTURE WORK

We need to study using invariant detectors or automatically varying the self-samples, so that a single sample covers the cases of viewing under different illumination or an affine transformation. Invariant detectors would correspond to non-spherical shapes in feature space. These geometrical aspects should be investigated to see what effects they have on AIS performance. A desirable application specific modification is to give each local detector a means of enforcing global geometric constraints, perhaps through a cellular autonoma-like mechanism. We want to only identify road pixels that are consistent with the knowledge that roads are long, thin, fairly straight, and connected to each other. Ideally, the sample data implicitly specifies this knowledge.

Also, some factors affecting user interaction with the AIS need investigation. For example, how large a sample size is sufficient? Given an adapted AIS, if the output is unsatisfactory, what are good algorithms for adding or removing samples? Many randomly generated detectors respond to the sample set and must be removed. What are efficient algorithms to generate new detectors? Generating some of the trial detectors randomly and some as mutations of successful detectors could speed up convergence, yet still maintain required variability. One measure of the efficiency of detector generation is the degree of overlap in the detector population. We need to measure overlap and find ways to reduce it, if necessary. Detector overlap as it applies to cross-reactive immune memory is studied in detail by [11]. Lastly, we should evaluate a Network Theory AIS for this application, too.

CONCLUSION

This study demonstrates the feasibility of Artificial Immune Systems for supervised aerial image segmentation. An AIS was able to locate road pixel candidates using simple local detectors and a small amount of hand-classified sample imagery. Negative selection is vastly superior to random search. The AIS paradigm of finding a detector population that weeds out everything but the desired class is an advantage in processing natural imagery since positive samples of the desired class are typically available, but the variation in natural imagery precludes using negative samples of every possible undesired feature. This initial demonstration, while promising, shows more work is necessary to model and fully develop AIS as a useful tool for aerial and satellite image segmentation.

ACKNOWLEDGMENTS

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FIGURES

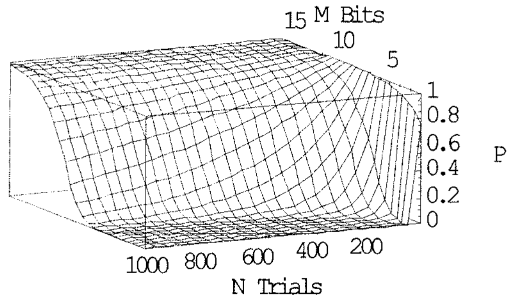


Fig. 1 - Probability P of not finding correct M bit detector after N trials of a random search.

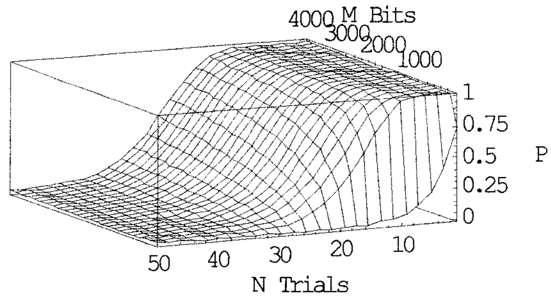


Fig. 2 - Probability P of detector population not being correct after processing N randomly generated detectors.

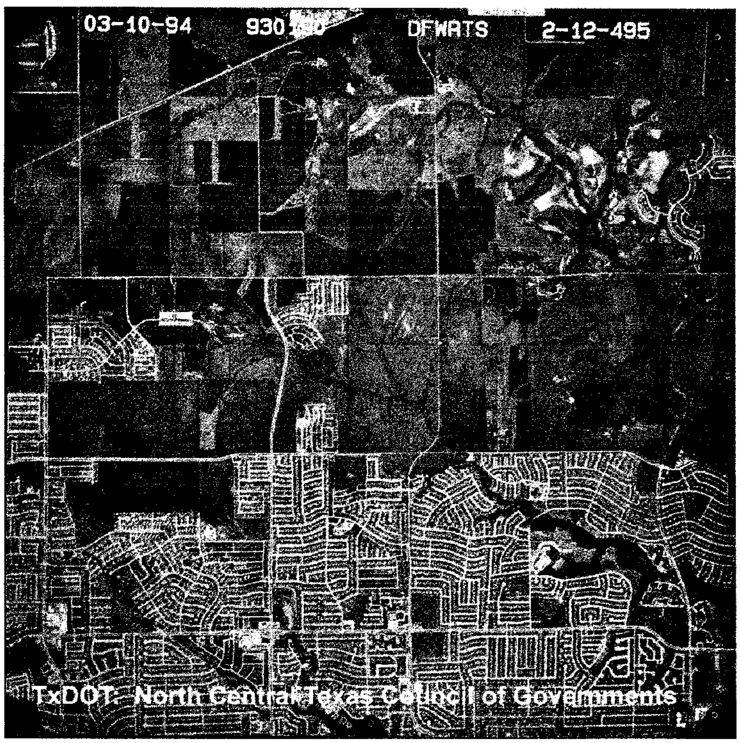


Fig 3 - Original Aerial Image

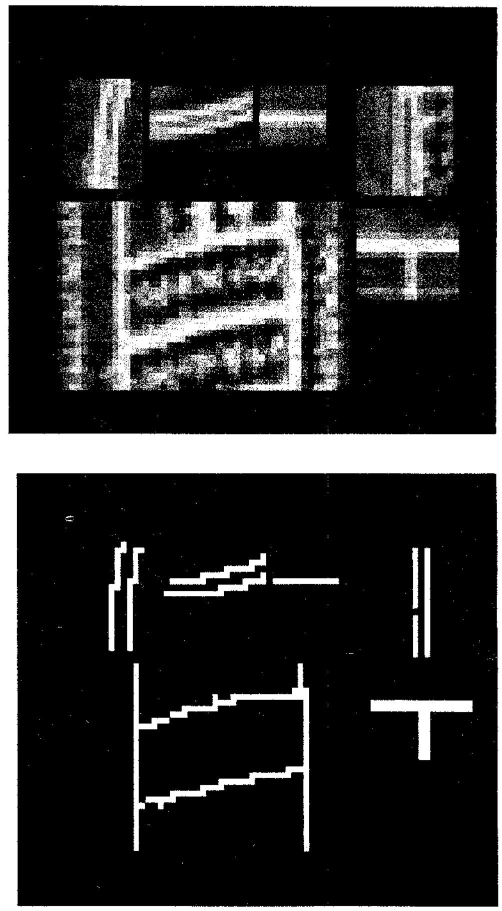
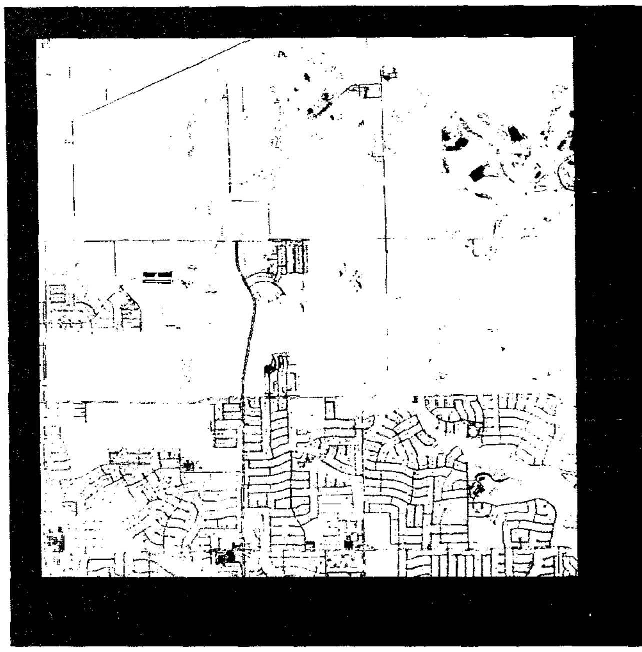


Fig 4 - Sample Data and Classification



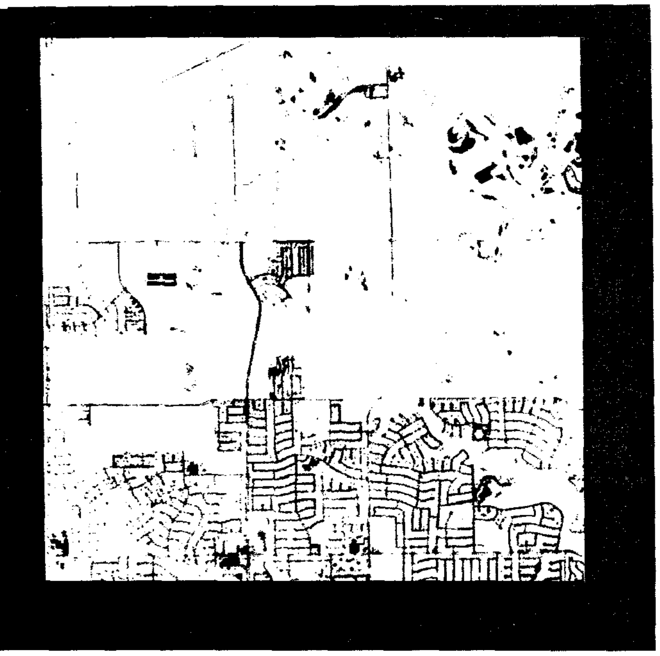


Fig. 5 - 3x3 Pixel Detector

Fig. 6 - 5x5 Pixel Detector

Fig. 7x7 Pixel Detector

Fig. 9x9 Pixel Detector