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# The Multi-Sensor Fusion: Image Registration Using Artifical Immune Algorithm

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**Abstract** – ***The immune system is a cognitive system of complexity comparable to the brain and its computational algorithms suggest new solutions to engineering problems. Using immunological principles, an artificial immune algorithm is presented for the multi-sensor fusion - image registration problem. The method uses receptor editing to escape from the local optima. The method applied to the registration problem shows good convergence results to the global minimum. Experimental results show the method to be efficient even in the presence of large amounts of noise.***

## I. INTRODUCTION

Sensors are used to provide a system with useful information concerning some features of interest in the system's environment. Multisensor fusion refers to the synergistic combination of sensory data from multiple sensors to provide more reliable and accurate information. Multiple sensor networks have been divided into complementary, competitive, and cooperative configurations. Particularly competitive multiple sensor networks consist of a large number of concrete sensors providing readings that are at least partially redundant. The first step in fusing multiple sensor readings is to find the correspondence between them. In order to fuse two sensor readings, the readings must first be put into a common coordinate system. Very often someone assumes that the relationship between two readings is known a priori. This assumption is unwarranted in a large number of dynamic systems. Let us consider the task of finding the correct mapping of one image onto another, also known as image registration (any two-dimensional sensor reading can be represented as an image). In the past years, several methods for image registration such as Tabu Search, genetic algorithm (GA) and simulated annealing (SA) have been presented [1]-[5]. Tabu Search is often used as an alternative to SA. GA is computational paradigm that has been implemented successfully as a solution to many optimization problems. The genetic algorithm using the elitist reproduction scheme often found close to globally optimal results [2]. Each algorithm has its features and disadvantages [4]: Tabu Search reaches a decision rapidly, although usually to the local optimum; finding a clear stopping criteria for Tabu Search is impossible; GA reaches the global optimum with more calculation; and the process for reaching the global optimum is dependent on the initial conditions.

In this paper, we proposed an artificial immune method for image registration. The immune system, with its cell diversity and variety of information processing mechanisms, is a cognitive system of complexity comparable to that of the brain. Interest in studying the immune system has been increasing over the last few years, and a new field of research called artificial immune systems has arisen [6], [7]. In [8] the authors proposed an efficient artificial immune algorithm for solving optimization problems. We present a detailed analysis of the artificial immune system's implementation for registering images along with examples.

## II. IMAGE REGISTRATION

Multiple sensor systems receive readings from different positions and orientations. To fuse multiple sensor readings, they must be registered into a common coordinate system. The problem addressed in this paper was originally posed in reference [2]: Given two N-dimensional sensor readings, it is necessary to find the function F which best maps the readings from sensor two $S_2(x_1, x_2, \ldots, x_n)$ onto the readings from sensor one $S_1(x_1, x_2, \ldots, x_n)$. In practice, all sensor readings contain some amount of measurement error or noise so that the ideal case will rarely occur, if ever. The goal is to find the optimal parameters $(x_T, y_T, \theta)$ that define the relative position and orientation of the two sensor readings. The search space is a three-dimensional vector space defined by these parameters, where a point is denoted by the vector $w=[x_T, y_T, \theta]^T$. Fig. 1 and equation (2.1) show the transformation between the two images.

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta & X_T \\ \sin\theta & \cos\theta & Y_T \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \qquad (2.1)$$

When noise in the sensor data has a Gaussian distribution, we have derived the fitness function [1] in equation (2.2):

$$\frac{\sum (read_1(x,y) - read_2(x',y'))^2}{K(W)^2} \qquad (2.2)$$

Where: $W$ is a point in the search space; $K(W)$ is the number of pixels in the overlap for $W$; $read_1$ and $read_2$ are the pixel value returned by sensor 1 and sensor 2.

Therefore, we seek the value of $x_T$, $y_T$, and $\theta$ that provide the globally minimal value for (2.2).

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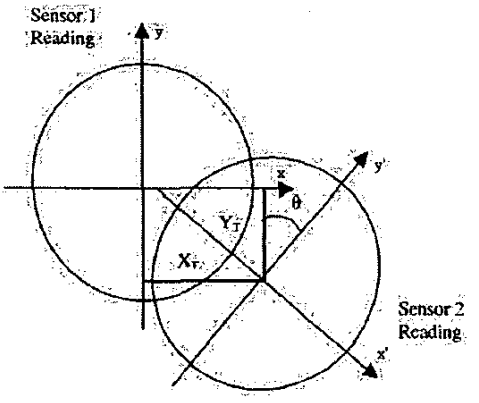


Fig.1 Geometric relation of two sensor readings

## III. ARTIFICIAL IMMUNE ALGORITHM

The immune system (IS) is a complex of cells, molecules and organs that represents an identification mechanism capable of perceiving and combating both dysfunction from our own cells (*infectious self*) and the action of exogenous infectious micro-organisms (*infectious nonself*). The interest in studying the immune system is increasing over the last few years. Computer scientists, engineers, mathematicians, philosophers and other researchers are interested in the capabilities of this system, whose complexity is comparable to that of the brain. A new field of research called artificial immune systems has arisen. The scope of the application of artificial immune systems includes computer security, anomaly detection and fault diagnosis, pattern recognition, optimization, image and signal processing and controls, etc [9].

According to the basic features of an adaptive immune response to an antigenic stimulus, de Castro and Von Zuben proposed a computational implementation of the clonal selection principle [8] that explicitly takes into account the affinity maturation of the immune response. It establishes the idea that only those cells that recognize the antigens proliferate, thus being selected against those that do not. Clonal selection operates on both T cells and B cells. In a T-cell-dependent immune response, the repertoire of antigen-activated B cells is diversified basically by two mechanisms: hypermutation and receptor editing.

It is necessary that two different mechanisms are used to introduce diversity during an immune response. Receptor editing offers the ability to escape from local optima on an affinity landscape. Fig. 2 illustrates this idea by considering all possible Antigen-binding sites depicted in the axis, with the most similar ones adjacent to each other. The antigen–antibody affinity is shown on the vertical axis. If a particular antibody (Ab) is selected during a primary response, then hypermutations allow the immune system to explore local areas around by making small steps toward an Ab with higher affinity, leading to a local optimum. Because mutations with lower affinity are lost, the Ab's tend to go uphill. Receptor editing allows an Ab to take large steps throughout the landscape, possible landing in a locale where the affinity might be lower. However, occasionally the leap will lead an Ab to a side of a hill where the climbing region is more promising, reaching the global optimum. From this locale, hypermutations can drive the Ab to the top of the hill. In conclusion, hypermutations are good for exploring local regions, while receptor editing may rescue immune responses stuck on unsatisfactory local optima.

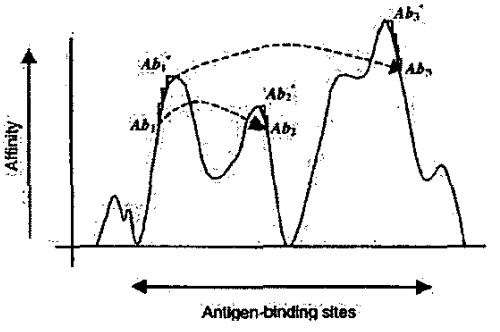


Fig. 2. Schematic representation of shape space for Ag-binding sites. Somatic mutations guide to local optima, while receptor editing introduces diversity, leading to possibly better candidate receptors.

In addition to somatic hypermutation and receptor editing, a fraction of newcomer cells from the bone marrow is added to the lymphocyte pool in order to maintain the diversity of the population. This may yield the same result as the process of receptor editing, i.e., a broader search for the global optimum of the antigen-binding site.

To quantitatively describe the interactions between immune cell molecules and antigens (Ag), the Hamming shape-space is introduced. The affinity between an antigen and an antibody is related to their distance, which can be estimated using Hamming distance measure between two strings (or vectors). If the coordinates of an antibody are given by $<ab_1, ab_2, ..., ab_L>$ and the coordinates of an antigen are given by $<ag_1, ag_2, ..., ag_L>$, then the distance ($D$) between them is presented in Equation (3.1).

$$D = \sum_{i=1}^{L} \delta, \delta = \begin{cases} 1 & if \quad ab_i \neq ag_i \\ 0 & otherwise \end{cases} \qquad (3.1)$$

There is no explicit Ag population to be recognized, but an objective function to be optimized (maximized or minimized) here. This way, an Ab affinity corresponds to the evaluation of the objective function for a given Ab, so that each Ab represents an element of the input space.

The algorithm works as follows (see Figure 3):

(1) Generate a set (P) of candidate solutions, composed of the subset of memory cells (M) added to the remaining (Pr) population (P = Pr + M);

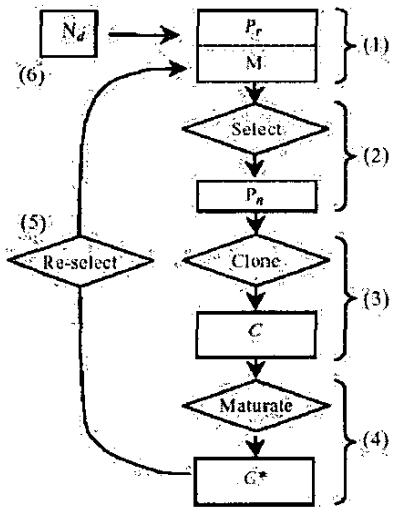


Figure 3: Block diagram of the algorithm implemented.

(2) Determine the $n$ best individuals, P$n$, of the population P, based on an affinity measure;

(3) Clone (reproduce) these $n$ best individuals of the population, giving rise to a temporary population of clones ($C$). The clone size is an increasing function of the affinity measure of the antigen;

(4) Submit the population of clones to a hypermutation scheme, where the hypermutation is proportional to the affinity of the antibody. A maturated antibody population is generated ($C^*$);

(5) Re-select the improved individuals from $C^*$ to compose the memory set. Some members of the P set can be replaced by other improved members of $C^*$;

(6) Replace $d$ low affinity antibodies of the population, maintaining its diversity.

## IV. EXPERIMENT RESULTS

We use the synthesized image given by the equation [2]:

$$f(x,y)=100+\frac{1}{100}\left(-40x+45y-0.003xy+0.002x^2-\right.$$
$$-0.001y^2-20y\sin\left(\frac{x}{18}\right)+35y\cos\left(\frac{y}{29}\right)-$$
$$\left.-35\sin\left(\frac{x}{4}-\frac{y}{12}\right)+12x\cos\left(\frac{xy}{100}\right)\right) \qquad (4.1)$$

This image has several periodic and non-periodic components.

### *A. One-Dimensional Case*

We chose to use the rotation parameter $\theta$ for the one-dimensional test. $\theta$ is a continuous variable. Two sensor readings are cut from the terrain image. Sensor one is centered at (256,256), sensor two is centered at (256,256) with different rotation for some experiments.

Table1. Artificial immune algorithm search results

Sensor 1 position: $x$=256,$y$=256,$\theta$=0
Sensor 2 position: $x$=256,$y$=256,$\theta$=2.8798
Population size of antibody: 15 Mutation probability: 0.020
Number of clones per candidate: 3 Noise level: 0

| Number of Iteration | Current $\theta$ | Value of Fitness Function | Number of Antibody | Current $\theta$ Error |
|---|---|---|---|---|
| 1 | 6.1443 | 0.03129 | 1 | 113.36% |
| 15 | 2.8686 | 0.00656 | 2 | -0.39% |
| 30 | 2.8701 | 0.00655 | 4 | -0.34% |
| 45 | 2.8705 | 0.00655 | 6 | -0.32% |
| 60 | 2.8755 | 0.00653 | 9 | -0.15% |
| 63 | 2.8759 | 0.00653 | 12 | -0.13% |

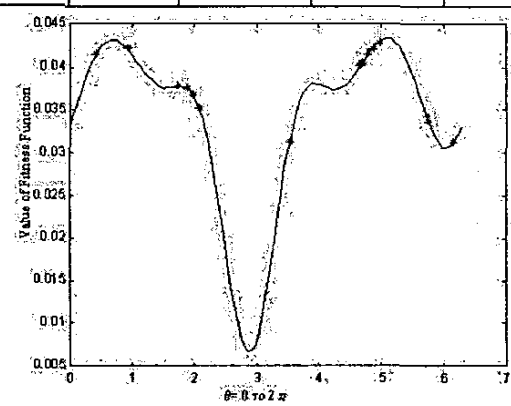


Fig.4 Initial antibodies population

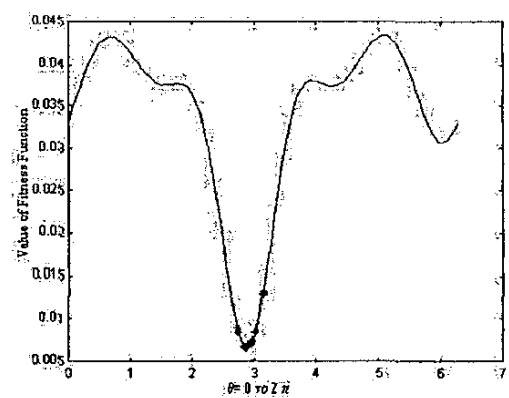


Fig.5 Final antibodies population

Table 1 and Fig.4-6 show the result of one of our experiments.Fig.4 shows the initial position of Abs that are randomly generated. Fig.5 shows the search result when 12 Abs have converged at the global minimum. From Fig.6, it is

evident that the global minimum was almost identified within 20 iterations.

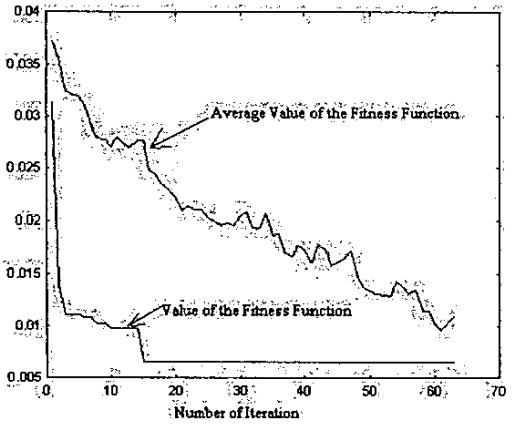


Fig.6 One-dimensional search results

Since we use the Ab to find the global minimum, it is not necessary that all Abs converge the global minimum to define the result to be solved. When the 80% of Abs converge at a point, that means this point is the one we search for.

Using the same parameters as in Table 1, several tests have been run with varying levels of noise. Fig. 7 shows the fitness function under various noise levels. The fitness function surface flattens as noise increases. The minima become less significant and the search becomes more difficult. But as shown in Table 2, artificial immune algorithm handles noise well in the one-dimensional case. When the ratio of signal-to-noise is 100%, the error of $\theta$ is just slightly more than 1%.

Table2 One-dimensional results under different noise levels

| Noise level | $\theta$ value | No. of Iteration | Fitness value | $\theta$ error |
|---|---|---|---|---|
| 0 | 2.883095 | 74 | 0.003254 | 0.1148% |
| 20 | 2.883062 | 53 | 0.003690 | 0.1136% |
| 40 | 2.883183 | 52 | 0.004844 | 0.1178% |
| 60 | 2.883106 | 47 | 0.005991 | 0.1151% |
| 80 | 2.885541 | 75 | 0.011044 | 0.1997% |
| 100 | 2.910921 | 151 | 0.020582 | 1.0810% |

*B. Multidimensional Case*

The search space in the three-dimensional case is: $-255<x<255$, $-255<y<255$, $0<\theta<2\pi$. Table 3 and Fig. 8 show the result by clonal selection algorithm. After 100 iterations, the results have converged to the global minimum. We have tested the clonal selection algorithm using noise with different variances under different conditions. Table 4 shows our results. We compare the results from the elitist GA [2], as show in Table 5.

From Table 4 and Table 5, both the immune algorithm and the elite GA can handle noise with a variance of up to 30. But the artificial immune algorithm results show the optimal

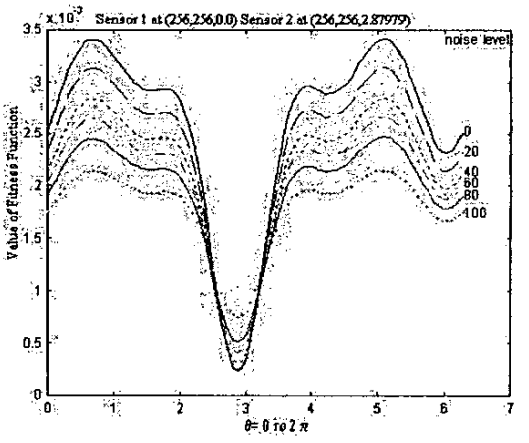


Fig.7 Objective function under different noise level

value can be found even in the presence of large amounts of noise. When the noise reaches levels such as 70 or 90, as shown in Table 4, it obscures the images and it becomes very difficult to find the correct answer.

Table3 Multidimensional artificial immune algorithm search results

Sensor 1 position: $x$=0,$y$=0,$\theta$=0
Sensor 2 position: $x$=91,$y$=91,$\theta$=2.748891
Population size of antibody: 15 Mutation probability: 0.020
Number of clones per candidate: 3 Noise level: 0

| Iteration | Current θ | $X$ value | $Y$ value | Value of Fitness Function | Number of Antibody |
|---|---|---|---|---|---|
| 1 | 2.697699 | -17 | 73 | 0.020548 | 1 |
| 20 | 2.690140 | 77 | 85 | 0.009007 | 1 |
| 40 | 2.736567 | 88 | 89 | 0.005864 | 2 |
| 60 | 2.736567 | 88 | 89 | 0.005864 | 2 |
| 80 | 2.739539 | 88 | 89 | 0.005669 | 4 |
| 100 | 2.743074 | 90 | 91 | 0.005225 | 6 |
| 120 | 2.743074 | 90 | 91 | 0.005225 | 7 |
| 160 | 2.743074 | 90 | 91 | 0.005225 | 9 |
| 282 | 2.743074 | 90 | 91 | 0.005225 | 12 |

## V. CONCLUSION

This paper discussed the use of the artificial immune method (proposed by de Castro et al. [8]) as a deterministic optimization algorithm to solve a sensor fusion problem. It approaches optimization by hypermutation of the antibodies, and utilizes receptor editing to escape from local optima on an affinity landscape. The artificial immune algorithm shows very good results in optimizing one-dimensional optimization problems, and encouraging results are also obtained in the multi-dimensional problem. The artificial immune algorithm

finds globally optimal answers even in the presence of large amounts of noise.

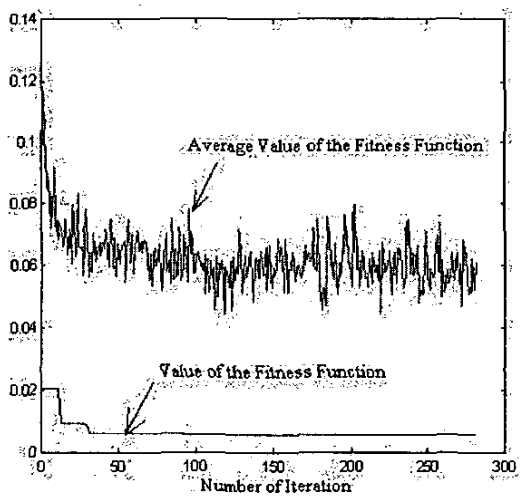


Fig.8 Multi-dimensional search results

Table 4 Results under Different Noise Levels

| Noise level | $X$ value | $Y$ value | $\theta$ value | Function value |
|---|---|---|---|---|
| 0 | 90 | 91 | 2.743074 | 0.005225 |
| 10 | 91 | 90 | 2.743910 | 0.006494 |
| 20 | 92 | 90 | 2.754197 | 0.009794 |
| 30 | 92 | 88 | 2.749673 | 0.014832 |
| 50 | 84 | 87 | 2.761557 | 0.017901 |
| 70 | 93 | 89 | 2.735764 | 0.020238 |
| 90 | 73 | 79 | 2.792830 | 0.024484 |

Table 5 Elite Genetic Search Results under Different Noise Levels[2]

| Noise level | $X$ value | $Y$ value | $\theta$ value |
|---|---|---|---|
| 0 | 89 | 91 | 2.74744 |
| 10 | 92 | 92 | 0 |
| 20 | 91 | 91 | 2.74744 |
| 30 | 89 | 89 | 2.74744 |
| 50 | 86 | -18 | 2.79768 |
| 70 | -48 | 6 | 6.02138 |
| 90 | 0 | 5 | 1.23297 |

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