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APPLICATION OF IMMUNE ALGORITHM IN MULTIPLE SENSOR SYSTEM

by

ZHENGQIAO JI

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Submitted to the Faculty of Graduate Studies and Research
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Canada

ABSTRACT

Recently the human immune systems have aroused researcher's interest due to it useful mechanisms which can be used exploited for information processing in a complex cognition system. The scope of this research is not to reproduce any immune phenomenon accurately, rather to show that immune concepts can be applied to develop powerful computational tools for data processing. From this viewpoint, an improved artificial immune algorithm is presented and applied in the problems associated with image registration and configuration of multiple sensor systems. The simulation results show that the immune algorithm can successfully obtain the global optimum with lesser computational cost compared to other traditional algorithms. Therefore this method has a potential application in other optimization problems.

ACKNOWLEDGEMENT

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Finally, my deep acknowledgements and thanks must be directed to my patient and understanding family and aunts. Their love has always encouraged me to move forward and remain focussed in a foreign country.

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CHAPTER I

INTRODUCTION

1. Multiple sensor fusion

Multiple sensor fusion is an evolving technology concerned with the problem of combining the information from multiple sensors in order to make an optimal system for inferences about a physical event or environment. In recent years, multiple sensor data fusion, as a new discipline, has been developed to solve a diverse set of problems having common characteristics in the sensor network.

The role of multiple sensor fusion can best be understood with reference to the type of information that the integrated multiple sensors can uniquely provide the system. The potential advantages gained through the synergistic use of this multiple sensor information can be decomposed into a combination of four fundamental aspects: the redundancy, complementarities, timeliness and the cost of the information.

2. Fusion application

Possible applications of multiple sensor fusion include virtually all systems involving signal processing. In modern industrial societies that rely heavily on communications and information, reliable data collection and interpretation is of utmost importance. Data fusion is therefore becoming an essential part of the modern decision-making processes.

Figure 1.1 presents a radar tracking system requiring multiple sensor fusion. This system consists of several independent radar sites to track airplane. Each reading consists of the location of an airplane in three dimensions, along with the airplane's velocity

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expressed in three dimensions. The data in the system is therefore concerned with at least four dimensions.
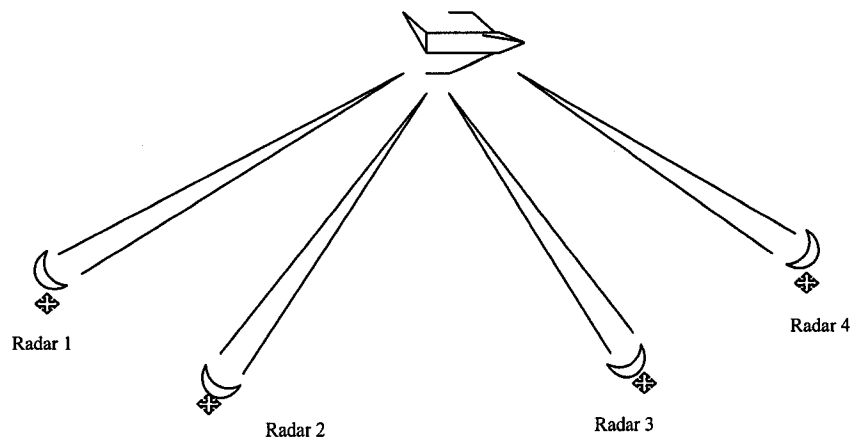
Figure 1.1: Multiple sensor fusion-Radar tracking

Other application areas include automation industries where accuracy and reliability are of paramount importance. In short, all applications that require reliable data processing to interact with a continuously changing environment can make good use of this technology, which means multiple sensor fusion can be applied into several main aspects as follows.

Aeronautics: As the number of airplanes in the air increases, air traffic control becomes more and more difficult. In order to track large numbers of aircraft over a large area, using more than one radar antenna is necessary. In order to avoid system downtime, a reasonable approach is to use redundant radar antenna in some critical areas.

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Airliners also rely on input from many different sensors i.e. navigation beacons, radar, altimeters and other equipment for accurately and reliably locating the position of the aircraft. These gadgets must be used in combination by the pilot in order to properly navigate large commercial airplanes. The same concerns exist for automatic navigation systems, which are in common use. Spacecrafts have to consider all the above factors and several others as well, such as resistance ability to noisy environments [1].

Manufacturing: Use of industrial robots in manufacturing has significantly increased worker productivity and the quality of the end product. One of the main problems that need to be resolved is that robot's sensors are not reliable. Sensor fusion is likely to help robots get reliable information about their environment.

Remote sensing: Remote sensing is one application area of technology that has seen tremendous growth within the last few decades. Satellites and airplanes use remote sensing devices for activities that affect the day-to-day human life. Remote sensing is used to provide accurate weather forecasting including charting the movement of hurricanes. A network of satellite is used to provide national intelligence service with accurate information that would otherwise be impossible to obtain. Satellites use remote sensing to determine how the environment is changing and study the effects pollution on the eco-system. Sensor fusion will help these applications be more accurate and less costly [2].

Work in hazardous environment: In order to avoid risking human life, many autonomous and semi-autonomous devices are being developed and used for working in hazardous areas. These devices must be particularly robust in order to function in special locations [3]. The military is also making use of unmanned guided vehicles for several

applications. During the desert storm operation, unmanned flying vehicles were used to provide intelligence about enemy troop positions on the battlefield. It is also meaningful in scientific research, such as volcano exploration.

Medical applications: with the development of modern hospitals, new tools and techniques for diagnosing illnesses are continuously emerging. It requires more sophisticated information regarding the health of the patient and operations will require technology that is extremely precise and beyond the manipulative abilities of unaided human hands. Accurate and reliable sensors are the key to obtain precise information needed for such diagnosis. Similarly the tools to perform surgical modifications at a microscopic scale must be used in coordination with very precise, accurate and reliable sensors. Sensor fusion is one of the important areas of research needed for further development in the field of medical technology [4].

3. Sensor and sensor data

A simple sensor can be represented by a single thermometer that returns a single reading with certain accuracy. It means sensor interacts with the environment and gives us a reading that is within certain bounds of inaccuracy.

Mathematical model of a simple sensor is shown below. The mathematical function has two arguments, the environment E and time t. The function, S maps the environment to numeric values represented as variable V. V is a point in a D-dimensional space. V is surrounded by an uncertainty ε.

$$S(E,t) = \{V(t), \varepsilon(t)\}$$

An analysis of sensor performance results concludes that there isn't a perfect sensor, i.e., no single sensor or type of sensor accurately detects, locates, and identifies

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targets in all circumstances (namely, for all ranges, sensing environments, etc.). Some sensors are more accurate at locating and tracking objects, while others are good at providing identity information.

The main characteristics of sensors can be categorized into three aspects [5]:

Uncertainty and accuracy: sensors have varying accuracy. Rarely sensors provide one single, absolutely accurate value for a physical variable. When a sensor delivers this type of reading, the physical values being measured generally vary over time. A sensor reading that covers a finite time period would thus return a value range in order to accurately represent the environment. As commonly known, all data processing has its own limited accuracy i.e. all data representations have upper and lower bounds for the values that can be represented and a maximum number of digits of accuracy. If limits in accuracy are not handled properly, the key information can be lost, thus resulting errors in further calculation.

Probability and reliability: in addition to the limited accuracy of each sensor, the fact remains that a sensor might fail during the system's lifetime, or may temporarily return false readings for any possible reason. In other words, no matter how well a sensor is maintained, it will inevitably cause problem in its lifetime, especially under some hostile and noisy conditions. For these reasons, each sensor has an associated probability, which depends on the sensor type, environment and actual sensor reading at any given time.

Cost: each sensor also has its own cost. The cost of sensor is important in designing sensor network, since overpriced sensor systems cannot be put into practical

use. We regard cost as one of the attributes of sensors and take cost constraints into consideration during the design of a sensor network.

4. Benefits of sensor fusion

The purpose of multiple senor fusion is to obtain more accurate and reliable information of the observed target, which provides higher fault tolerance and dispensability than a system composed of one sensor. There are numerous examples where sensor fusion is used in industrial and commercial applications. For improved detection, effective integration of multiple sensor measurements of the event/target increases the chances of its detection. Besides, a system employing different sensors to measure various portions of the electromagnetic spectrum is less vulnerable to disruption by hostile action and natural phenomena. Therefore the benefits of sensor fusion include improved operational performance, extended spatial coverage, extended temporal coverage, increased confidence, reduced ambiguity of inferences, improved detection and enhanced system reliability [6].

In addition to the qualitative benefits mentioned above, the quantitative advantages of multiple sensor fusion can also be illustrated through an example shown in Figure 1.2 [7].

The lower curve gives the detection probability for a single radar sensor as a function of signal-to-noise ratio when the false alarm probability is 10^{-6}. The detection probability of 0.7 is acceptable while signal-to-noise locates on 16dB. But the detection probability drops to 0.27 when signal-to-noise falls to 10dB. Now assuming that a three-sensor radar system works under the same conditions, where each sensor responds to a

unique signature-generation phenomena and does not generate false alarm on the same events as others, then the false alarm rejection can be distributed among the three sensors. The system false alarm probability is recovered through some fusion methods that incorporate sensors operating in series and parallel combinations. When the false alarm rejection can be divided equally among the sensors, the radar performance is given by the upper curve marked with 10^{-2} false alarm probability. Now the nominal target signature
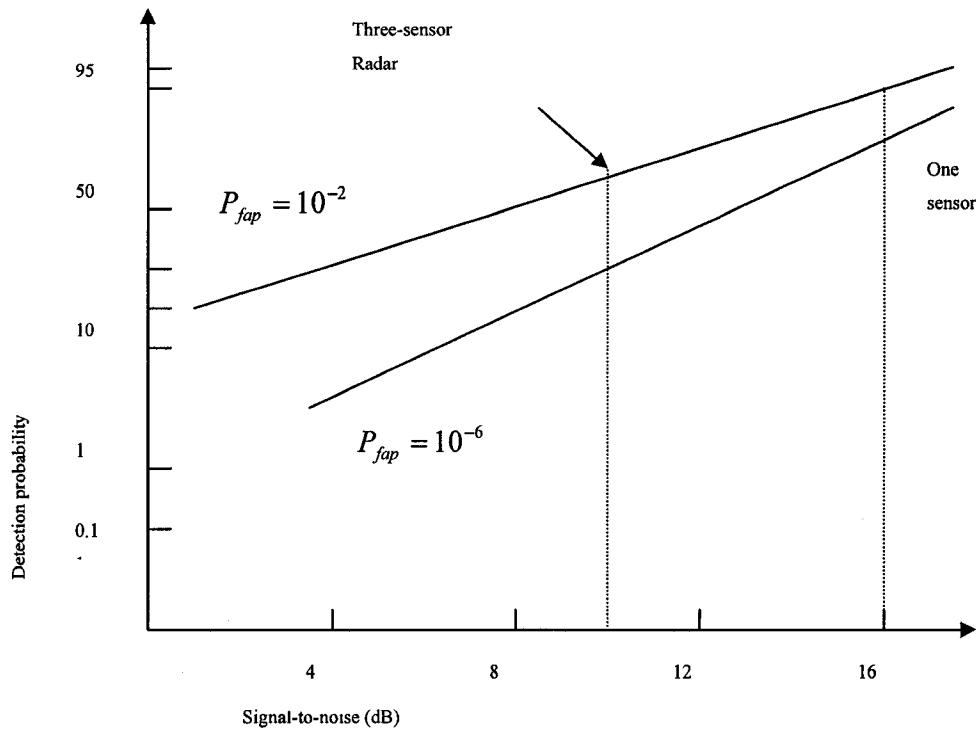
Figure 1.2: Multiple sensor system vs. Single sensor

yields a detection probability 0.85. Besides, the reduced signature target on signal-to-noise 10dB yields a detection probability 0.63, which is greater than before. The three-sensor system allows the false alarm rejection to be spread over the signature acquisition

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and signal processing capabilities of all sensors and data combining capabilities of the fusion algorithm.

5. General approach

The synergistic use of multiple sensors by machines and systems is a major factor in enabling some measure of intelligence to be incorporated into their overall operation so that they can interact with and operate in an unstructured environment without complete control of a human operator. The sensors in an intelligent system provide sufficient information of outside world for next operation and allow a system to learn the state of the world needed to continuously update its own model of the world. Therefore, it naturally leads people to a simple question: since a sensor can increase the capability of a system, how we can fuse more sensors to increase it even further? Over the past decade a number of researchers have devoted themselves to exploring this question from both a theoretical and practical perspective. Multiple sensor machines and systems have been built for use in a variety of areas of application, such as target recognition, mobile robot navigation and target tracking [8].

Although the process of multiple sensor fusion can take different forms depending on the particular needs and design of the overall system, certain basic functions are common to most implementations. Figure 1.3 illustrates these basic functions of multiple sensor fusion.

A group of n sensors provide input to the fusion process. In order to make readings from each sensor useful for fusion mechanism, the sensory data must be effectively and accurately modeled. A sensor model represents the uncertainty and error
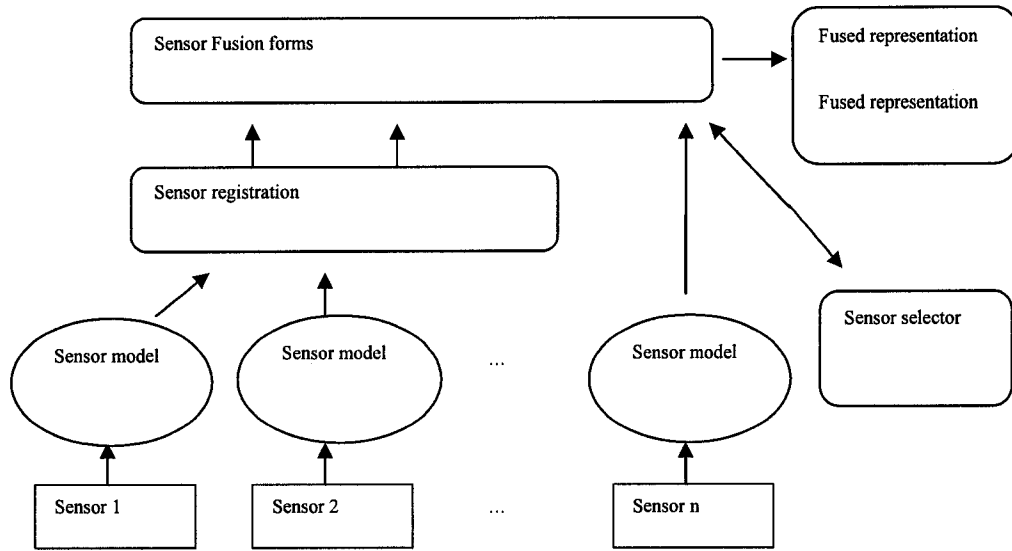
Figure 1.3: Basic Functions of Multiple Sensor Fusion

in the data from each sensor and provides a measure of its quality that can be used by the subsequent fusion functions. A common assumption is that the uncertainty in the sensor data can be adequately modeled as a Gaussian distribution. After data modelling the data is ready for further fusion processing. Sensor registration refers to the means used to make data from each sensor commensurate in both its spatial and temporal dimensions i.e. the data refers to the same location in environment over the same period of time. Sensor selector refers to the means adopted to select or allocate the particular group of sensors to be used by the system. Fusion forms will be discussed in the next chapter.

6. Sensor network motivation and challenge

Several different motivations exist for constructing a sensor network. In general, several independent sensors are combined into a network in order to obtain performance

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and capabilities one simple sensor is unable to achieve. These networks can have many different construction levels and different network architectures which have respective data communications and computational complexity requirements. They decide the ways sensors can interact and the interaction among sensors in turn determines exactly how fusion will be done on the readings from these sensors.

According to different network configurations, we can divide the sensor networks into three categories: complementary, competitive and cooperative.

Complementary: In this sensor network, sensors are independent and can be combined to provide a more complete image of the phenomena being monitored. The typical example is that every radar monitors one part of a region and these radars together provide complete information of that region by merging their individual observations.

Complementary networks may give a representation of data over a large area, or provide several aspects of the same phenomenon that can be used together for studying one phenomenon. In general, to fuse complementary data is not difficult since the data from independent sensors can be appended to each other providing a more complete mapping of the physical attributes being studied.

Cooperative: cooperative sensor networks combine data from independent sensors to derive information that would be unavailable from individual sensors. The interaction of sensors is sensitive to chrematistics of all simple sensors components used. The cooperative fusion causes accuracy and reliability of whole system to decrease when information from all simple sensor components is combined.

Competitive: in competitive sensor network, each sensor provides respective measurements of same information, regarding a physical phenomenon. Because they all

focus on same target, the sensors are in competition as to which reading will be adopted by the system in the case of discrepancies. The reason to use competitive sensor network is to provide greater reliability and fault-tolerance to a system.

In contrast to the example in a complementary network, if all radars monitor the same area and return their readings, the question raised is which is the exact information at the point measured and what is the accuracy of the measurement.

To sum up, complementary and independent sensor network are the most easily fused. Data from independent sensors can usually be inserted in to the same map structure as extra fields without any ill effects. Cooperative sensor networks take data from simple sensors and construct a new abstract sensor with data that does not resemble the readings from any particular sensor. This setup is a special construction of new information and is not limited to the reconciliation of the existing sensor data, which makes it more appropriate in the preprocessing stage.

The most difficult type of sensor fusion is one that involves data from competitive sensors, because this data is redundant and inconsistencies will arise between the sensor readings. These characteristics help improve the overall system performance based on the combination of different sensor readings. However, utmost care must be taken to fuse inconsistent data in a way that removes as much disturbances as possible in order to increase the robustness of the system. Otherwise, competitive data fusion may have potentially disastrous consequences.

7. Summary

This chapter provides an introduction to multiple sensor fusion problems and defines the basic terminology. A model of multiple sensor networks is introduced along

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with a summary of its applications, characteristics and advantages. Note that multiple sensor fusion is not a discipline in the same sense as a more well-defined study as signal processing or numerical methods because it still has space to develop an eclectic set of algorithms and techniques to solve a diverse set of problems.

CHAPTER II

MULTIPLE SENSOR FUSION

1. General framework

The fusion of multiple sensor data or information from multiple sensors can take place at different levels of representation. A classic categorization is to consider multiple sensor fusion taking place at signal, pixel, feature and symbol levels of representation since most of the sensors typically used in practice provide data that can be fused at one or more of these levels. Recently a generic framework covering a large set of these approaches has been given [9], [10]. A general framework is illustrated in Figure 2.1.

PT		Pixel-based	No grouping Or Scale-grouping	Pick Max	Verification Or Not
DWT		Window-based			
DWF		Region-based		Aver-age	

MSD representation   Measurement   Combination   Fused MSD
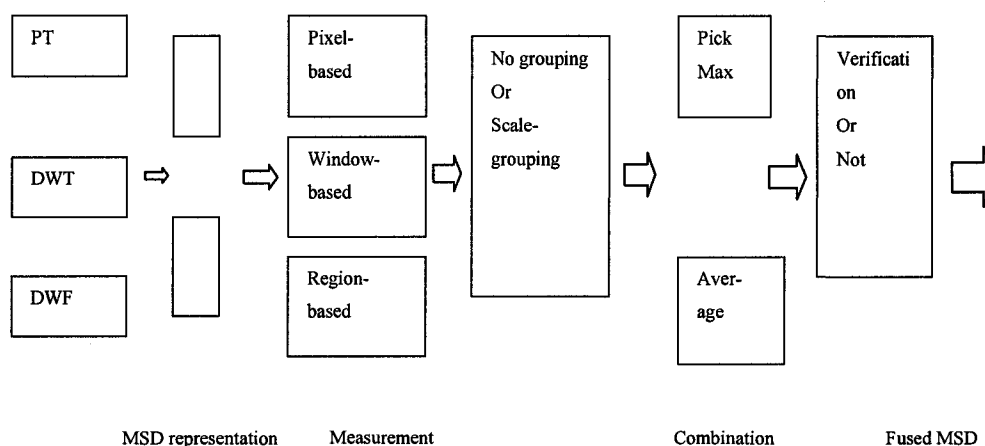
Figure 2.1: General Framework

In this figure, blocks in each column allow a choice of several alternatives. Selecting different choices will lead to the composition of different algorithms. For example, the first block contains three common transform for multiple scale

decomposition: pyramid transform (PT), discrete wavelet transform (DWT), and discrete wavelet frame (DWF). Of course, these three are not mandatory before executing next step so that the following steps are applied directly to the original signal as opposed to the transform. Whether to use transform or not and the nature of transform to be used varies from one case to another, sometimes using no transform does provide simplicity in many applications.

The other blocks in Figure 2.1 describe how each coefficient of the MSD representations of the source sensor information should be used to construct the MSD representation of the fused data. This process is influenced by a quantity we call the activity level measurement which attempts to determine the quality of each source data. Grouping methods allow the fusion process to consider groups of coefficients in each source data rather than considering a single coefficient at a time. In addition, combination methods describe exactly how the composite MSD representation of the fused information is obtained from the MSD representations of the source data, which are based on the previous steps. After a fused data is determined, further modifications can be made by a consistency verification procedure which incorporates the idea that a composite MSD coefficient is unlikely to be generated in a completely different manner from all its neighbours.

2. Mathematical tools

The study of computer science is primarily concerned with the study of data representations and their transformation by a software program. In the multiple sensor system, programs are manipulated to provide an accurate and relevant description of objects in the real world. According to the characteristics of sensor fusion, the program

must be different with traditional methods and linear programming. A number of methods have been proved to be practical algorithms for solving non-linear problems, such as tabu search, genetic algorithms, simulated annealing and artificial neuron network.

Tabu search: Tabu search is one of class of non-monotonic search methods that have been proposed for solving optimization problems. The optimization here refers to find globally optimal solutions in problems containing local minima. Optimization problems containing local minima are more difficult than linear problems that can be solved by linear programming.

The Tabu method was partly motivated by the observation that human behaviour appears to operate with a random element that leads to inconsistent behaviour given similar circumstances. In the tabu search category of meta-heuristics, the essential idea is to 'forbid' search moves to points already visited in the (usually discrete) search space, at least for the upcoming few steps. That is, one can temporarily accept new inferior solutions, in order to avoid paths already investigated. This approach can lead to exploring new regions with the goal of finding a solution by 'globalized' search. Tabu search has traditionally been applied to combinatorial optimization (e.g., scheduling, routing and traveling salesman) problems. The technique can be made, at least in principle, directly applicable to continuous global optimization problems by a discrete approximation (encoding) of the problem, but other extensions are also possible [11].

Simulated annealing: it is a simple Monte Carlo simulation that samples the possible states of a system by randomly choosing new parameters while attempting to find optimal answers to problem in a manner analogous to the formation of crystals in

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cooling solids. A material heated beyond a certain point will become fluid; if the fluid is cooled gradually, the material will form crystals and revert to a minimal energy state. The strategy of this algorithm is based on a fitness function comparing the relative merit of various points in the problem space. A Simulated Annealing optimization starts with a Metropolis Monte Carlo simulation at a high temperature. This means that a relatively large percentage of the random steps that result in an increase in the energy will be accepted. After a sufficient number of Monte Carlo steps, or attempts, the temperature is decreased. The Metropolis Monte Carlo simulation is then continued. This process is repeated until the final temperature is reached.

A Simulated Annealing program consists of a pair of nested loops. The outer-most loop sets the temperature and the inner-most loop runs a Metropolis Monte Carlo simulation at that temperature. The way in which the temperature is decreased is known as the cooling schedule. In practice, two different cooling schedules are predominantly used; a linear cooling schedule ($T_{new} = T_{old} - \Delta T$) and a proportional cooling schedule ($T_{new} = C \times T_{old}$) where C<1.0. Actually, they are just the ones that appear the most in literature; other cooling schedules are shown in Figure 2.2.

From a point in the search space, a neighbouring point is chosen at random. The difference in the fitness function value between the new point and the current point is calculated. This difference is used together with the current system temperature to calculate the probability of the new position being accepted. This probability is given by

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the distribution $e = ^{-\Delta C / t}$. The process continues with the same temperature t either for a

$$T_i = \frac{A}{i+1} + B$$

$$A = \frac{(T_0 - T_N)(N+1)}{N}$$

$$B = T_0 - A$$
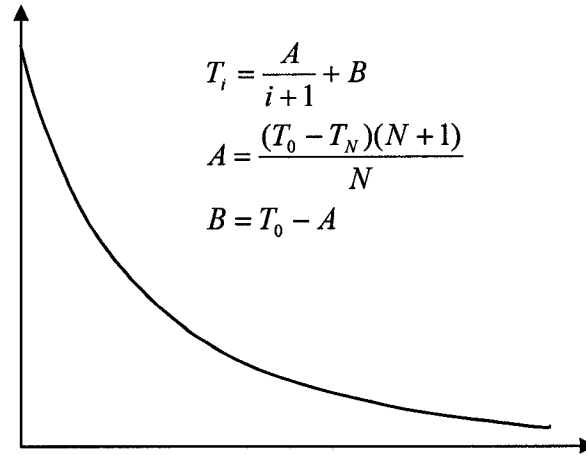
Figure 2.2: A Cooling Schedule

given number of iterations or until a given number of positions have been occupied, at

which time the value t is decreased. The temperature decreases until no transitions are

possible, so the system remains frozen in one position. This freezing occurs only when

ΔC is positive for all neighboring points: therefore, the position must be a local

minimum and may be the global minimum, showing that simulated annealing has a

definite halting condition as opposed to tabu search and genetic algorithms. Although this

is advantageous for many applications but the result may be still the local optima.

Genetic algorithm: Genetic algorithm attempt to apply a Darwinian concept of

survival of the fittest to optimization problems, the idea being that biological systems

adapt themselves to fit into an ecological niche. The hypothesis is similar to evolutionary

process with a parametric description of an answer instead of a deoxyribonucleic acid

(DNA) code would result in a series of increasingly fit answers. Possible solution to a

problem is called chromosomes and a diverse set of chromosomes are grouped into a

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gene pool. The relative quality of these answers are determined and used in production of the next generation chromosomes. The contents of high quality solution are more likely to survive to next generation. The next generation is generally formed via the processes of crossover, combing elements of two chromosomes from the gene pool, mutation and randomly altering elements of a chromosome. Comparison between genetic algorithm and proposed method will be discussed in the following chapter.

Artificial neural network: Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain.

The most common type of artificial neural network consists of three groups or layers of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units (See Figure 2.3). The activity of the input units represents the raw information that is fed into the network while the activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units. The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active and therefore by modifying these weights, a hidden unit can choose what it represents.

We also distinguish single-layer and multi-layer architectures. The single-layer organization, in which all units are connected to one another, constitutes the most general case and is of more potential computational power than hierarchically structured multi-

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layer organizations. In multi-layer networks, units are often numbered by layer, instead of following a global numbering.
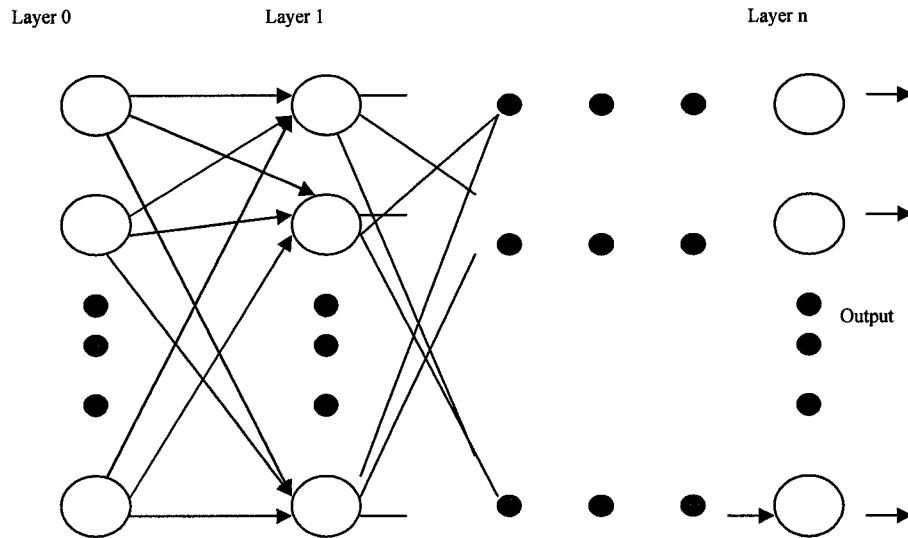
Figure 2.3: A Classic Artificial Neural Network

Artificial neural networks or shortly neural networks have been quite promising in offering solutions to problems, where traditional models have failed or are very difficult to build. Due to the non-linear nature of the neural networks, they are able to express much more complex phenomena than some linear modeling techniques.

Kohonen divides artificial neural networks into three categories [12]: 1) Signal transfer networks; 2) State transition networks; 3) Competitive learning networks. In signal transfer networks, the input signal is transformed into an output signal. The signal traverses the network and undergoes a signal transformation of some kind. The network has usually a set of pre-defined basis functions, which are parameterized. The learning in these networks corresponds to changing parameters of these basis functions. Some examples are the multi-layer perceptron (MLP) networks that are taught with error back

propagation algorithm (BP) and radial basis function (RBF) networks. More about these network models can be found in books [13], [14].

In state transition networks the dynamic behavior of the network is essential. Given an input, the network converges to a stable state, which, hopefully, is a solution to a problem presented to it. Examples are Hopfield networks and Boltzmann machines.

In competitive learning networks, or self-organizing networks, all the neurons of the network receive the same input. The cells have lateral competition and the one with most activity ``wins''. Learning is based on the concept of winner neurons. A representative example of a network based on competitive learning is the Self-Organizing Map. The monograph by Kohonen is the most complete book about this particular network model.

Learning in artificial neural networks is done in terms of adaptation of the network parameters. Network parameters are changed according to pre-defined equations called the learning rules. The learning rules may be derived from pre-defined error measures or may be inspired by biological systems. An example of an error measure in a network based on supervised learning could be the squared error between the output of the model and the desired output. This requires knowledge of the desired value for a given input. Learning rules are written so that the iterative learning process minimizes the error measure. Minimization might be performed by gradient descent optimization methods. In the course of learning, the residual between the model output and the desired output decreases and the model learns the relation between the input and the output.

The training must be stopped at the right time. If training continues for too long, it results in over learning. Over learning means that the neural network extracts too much

information from the individual case and forgets the relevant information of the general case.

3. Summary

In this chapter, we present the general process to deal with the problem of multiple sensor fusion. Besides, we also give a brief introduction to a number of tools and constructs needed for multiple sensor processing. The intention here is to give the reader a brief understanding of the various tools and their basic principles.

The methods mentioned above are related to the non-linear problems. Their applications for problems of multiple sensor fusion obtain satisfactory results in some cases.

CHAPTER III

FUNDAMENTAL OF IMMUNE SYSTEM

1. General ideas

Individuals who do not succumb to a disease when infected are said to be immune and the status of a specific resistance to a certain disease is called immunity. As the immune system plays a major role in the survival of humans/animals, it has to act efficiently and effectively. Researchers have found a lot of distinct components and mechanisms working on the immune system. Some of these elements are optimized to defend against a specific invader, while others are directed against a great variety of infecting agents. The circulation of immune cells as well as their traffic through the organisms is essential to immune surveillance and to an efficient immune response. In addition, there is a great redundancy within the immune system, to allow for many distinct defence mechanisms to be activated against a single agent.

From a biological and computational viewpoint, the presence of adaptive and memory mechanisms in the immune system is very important. The immune system owns the capability of extracting information from the infectious agents or environment and makes it available for future recognition in cases of re-infection by a similar agent.

2. Brief History and Perspectives on Immunology

As a relatively new science, the origins of immunology have been attributed to Edward Jenner who, in 1796, discovered that by introducing small amounts of vaccine, or cowpox, in an animal would induce protection against the often lethal disease smallpox. When Jenner discovered the process of vaccination, very little was known about functioning of the immune system. The discoveries of Robert Koch and other researchers

from the 19th century contributed to the development of the science of immunology, which proved that pathogenic micro organisms caused infectious diseases; each of which is responsible for a specific infection or pathology. In 1890, Emil von Behring and Shibasaburo Kitasato demonstrated that protection induced by vaccination was not due to the removal of nutrients, but was associated with the appearance of protecting elements in the blood serum of inoculated individuals. They discovered that people who had been inoculated against diseases contained certain agents that could in some way bind to other infectious agents. These agents were named antibodies.

From the beginning of 20th century, several theories related to the immune system had been proposed. Paul Ehrlich formulated a theory named side chain theory. The main premise of this theory was that the surfaces of white blood cells, such as B-cells, are covered with several side-chains, or receptors. The receptors on the surfaces of B-cells form chemical links with the antigens encountered. In a broad sense, any molecule that can be recognized by the immune system is regarded as antigen.

Furthermore, the providential theory intrigued by Ehrlich stated that antibodies might be constructed from the collection of genes, or genome, of the animal. Therefore, it was suggested that the content of a receptor on a B-cell with a given antigen would be responsible for selecting and stimulating the B-cell. This would give rise to large production of these receptors, which would then be secreted to the blood stream as antibodies.

Niels K. Jerne revived the selective theories of antibody formation in the early 1950. Jerne assumed that a diverse population of natural antibodies would appear during development, even in the absence of antigen interaction. The antigen would be matched

through the selection of circulating antibodies containing structures complementary to this antigen. The quality of an immune response to a given antigen would depend on the concentration of the circulating antibody of a specific type and could be enhanced by the previous exposition to the antigen.

In 1959, Burnet formalized the clone selection theory which asserts that each cell produces and creates on its surface a single type of antibody molecule [15]. The selective event is the stimulus given by the antigen, where those cells that produce antibodies complementary to it will proliferate (clone expansion) and secrete antibodies.

More recently, Susumo Tonegawa (1983) formalized his research concerning the structure and diversity of the antibody molecules, He proposed that within the genome of a germinal cell, a newly created cell, is contained (in multiple gene segments scattered along a chromosome) the genetic information to code or an antibody molecule.

According to Zinkernael's (2000) progress made in cell biology, genetics, molecular biology and developmental biology will help scientists to better understand general rules and exceptions of immunity. Also, among the many challenges for the immunology to the 21st century, Abbas and Janeway made a further step in the understanding of the mechanisms that control the adaptive immune response [16].

Table 3.1 below summarizes the main concepts, periods and their respective researchers.

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Table3. 1 Periods of History of Immunology

Fields	Period	Pioneers	Concepts
Application	1796-1870	E.Jenner R.Koch	Immunization Pathology
	1870-1890	L.Pasteur E.Metchnikoff	Immunization Phagocytosis
Description	1890-1910	E.von Behring P.Ehrlich	Antibodies Cell receptors
	1910-1930	J.Bordet K.Landseiner	Specificity/complement Haptens/Blood types
Mechanisms	1930-1950	A. Breinl L.Pauling	Antibody synthesis Instructionism
	1950-1980	M.Burnet N.Jerne	Clone selection Network and cell co-op
Molecular	1980-1990	S.Tonegawa	Structure and diversity of receptors

3. Fundamental s and Main components

The immune system is a natural, fast and effective defence entity against infections. It is composed of a two-tier line of defence, these are known as the innate immune system and the adaptive immune system. Both systems depend on the activity of white blood cells, the leukocytes, where the innate immunity is mediated mainly by granulocytes and macrophages, and the adaptive immunity is controlled by lymphocytes, as presented in Figure 3.1.

However, these two immunities play different roles in the immune system. The cells of the innate immune system are immediately available to combat against a wide variety of bacteria, without requiring previous exposure to them. This reaction will occur

in the same way in all normal individuals. The adaptive immune system refers to the production of antibodies in response to a determined infectious agent. In other words, antibodies are produced only corresponding to specific infections. The presence of antibodies in an individual reflects the infections to which that individual has already been exposed. Cells of the adaptive system are capable of developing an immune memory. They are also able to recognize the same antigenic stimulus when it is presented to the organism again. This capability avoids the re-establishment of the disease in the organism. Thus, the adaptive immune response allows the immune system to improve itself with each encounter of antigen.

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                          ┌─────────────┐
                          │  Immunity   │
                          └──────┬──────┘
               ┌─────────────────┴─────────────────┐
               ▼                                   ▼
        ┌──────────────┐                   ┌──────────────────┐
        │ Innate system│                   │ Adaptive system  │
        └──────┬───────┘                   └────────┬─────────┘
          ┌────┴─────┐                               ▼
          ▼          ▼                      ┌────────────────┐
   ┌──────────────┐ ┌──────────────┐        │  Lymphocytes   │
   │ Granulocytes │ │ Macrophages  │        └───────┬────────┘
   └──────────────┘ └──────────────┘            ┌───┴────┐
                                                ▼        ▼
                                          ┌────────┐ ┌────────┐
                                          │ B-cell │ │ T-cell │
                                          └────────┘ └────────┘
```
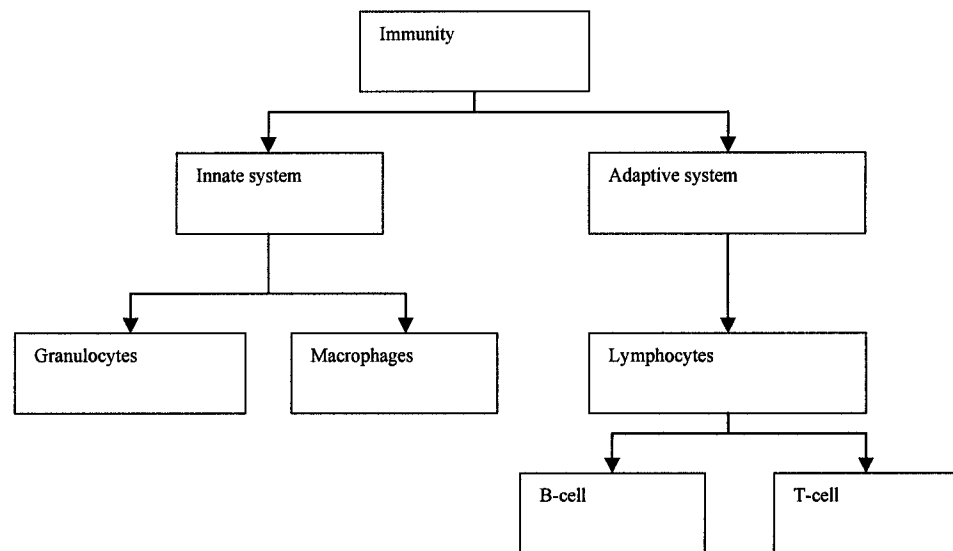
Figure 3.1: Inner Immune System and mediators

One of the important components in the immune system is the lymphocytes that mediate the adaptive immune response and are responsible for the recognition and elimination of the pathogenic agents. These agents are proportional to the immune memory that occurs after exposure to a disease. Lymphocytes usually become active

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when there is some kind of interaction with an antigenic stimulus leading to the activation and proliferation of the lymphocytes. There are two main types of lymphocytes: B lymphocytes (or B-cell) and T lymphocytes (or T-cell).

4. Basic Immune Recognition and Activation Mechanisms

While the innate and adaptive immune systems work together towards an extremely effective defence mechanism, the immune system needs a complex set of cells and molecules that protect our bodies against infection. Our bodies are under constant attack by antigens (Ag) that can stimulate the adaptive immune response. Antigens refer to all kinds of foreign cells, such as surface molecules on pathogens or self-antigens, which are composed of portions of cells or molecules within our body. Figure 3.2 illustrates a brief view of the main immune recognition and activation mechanism.

In the normal period, the specialized antigen presenting cells (APCs), such as macrophages, circulate throughout the body ingesting and digesting antigens. These antigens are fragmented into antigenic peptides. Part of these peptides bind to molecules of the major histocompatibility complex (MHC) which are in turn presented in the APC cell surface as an MHC/peptide complex. The T-cells carry surface receptors that allow them to recognize different MHC/peptide complexes. Once activated by the MHC/peptide, The T-cells become activated and promote other parts of immune system into action [17].

On the contrary, the B-cells have receptors that are possibly able to recognize the antigens without the helps of MHC molecules because the surface receptors on some B-cells respond to a specific antigen. When a pattern of antigen is recognized by these B-cell receptors, the B-cells are activated and proliferate and differentiate into plasma cells

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that secret antibody molecule in high volumes. These antibodies are used to neutralize the pathogen, leading to their destruction. Some of these activated B-cells and T-cells become memory cells for future protection against the same antigen.

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┌─────────────────┐      ┌─────────────┐      ┌─────────────────┐
│ APCs circulation │ ───> │  MHC bind   │ ───> │ MHC recognition │
└─────────────────┘      └─────────────┘      └─────────────────┘
                                                        │
                                                        ▼
                                               ┌─────────────────┐
                                               │ T-cell activation│
                                               └─────────────────┘
                                                        │
                                                        ▼
┌─────────────────┐      ┌─────────────────┐   ┌─────────────────┐
│Pathogen destruction│ <─ │B-cell proliferation│ <─│ B-cell recognition│
└─────────────────┘      └─────────────────┘   └─────────────────┘
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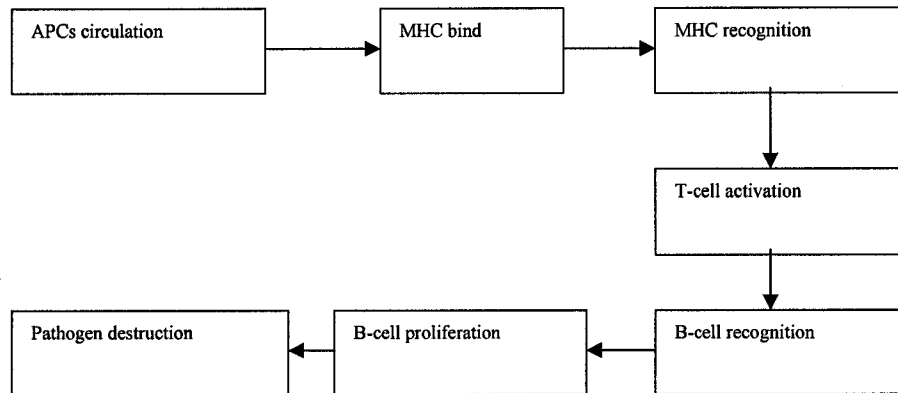
Figure 3.2: Immune Recognition and Activation Process

5. The Clone Selection Principle

In the adaptive immune response, the clone expansion is a process that allows an activated lymphocyte to proliferate and then differentiate into effective cells to fight against an infection.

The clone selection principle (or clone expansion principle) is the theory used to describe the basic properties of an adaptive immune response to an antigenic stimulus. It establishes the idea that only those cells capable of recognizing an antigenic stimulus will proliferate and differentiate into effective cells, thus being selected against those that do not. Clone selection operates on both T-cells and B-cells, B-cells suffer somatic mutation

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during reproduction and B-cells effectors are active anti body secreting cells. In contrast, T-cells do not suffer mutation during reproduction and T-cells effectors are mainly active lymphokine secretors. The presence of mutational and selection events in the B–cell clone expansion process allows these lymphocytes to increase their repertoire diversity and also to become increasingly better in their capability of recognizing the selective antigens. Mainly due to the genetic variation, selection, and adaptation capabilities of B-cells discussions will be focused on the clone selection of the B-cells.

Since each B-cell secretes only one kind of antibody for the antigen, antigenic receptors on a B-cell allow an antigen to stimulate a specific B-cell. The stimulation of the B-cell causes it to proliferate and mature into terminal antibody secreting cells called plasma cells in a lower rate. The B-cells, in addition to proliferation and differentiation into plasma cells, can differentiate into long-lived B-memory cells. Memory cells circulate through the blood, lymph and tissues and usually do not manufacture antibodies. However, when exposed to a second antigenic stimulus they rapidly commence differentiating into plasma cells capable of producing high affinity antibodies. These are pre-selected for the specific antigen that had elicited the primary response.

6. Immune Learning and Memory

The immune system must have efficient mechanisms to mount an effective response against pathogens since the antigen recognition only is not enough. Learning in the immune system involves raising the population size and affinity of those lymphocytes that have been proven themselves to be valuable during the antigen recognition phase. Thus the immune repertoire is biased from a random base to a repertoire that clearly reflects the actual antigenic environment [18].

The memory means that immune system can elicit a fast and accurate response against some known antigen rather than starting from scratch each time. This scheme is the result of successive infection or the intrinsic of learning strategy, where the system is continuously learning from direct interaction with the environment. We can simply regard the memory process of immune system as this way. The initial exposure to an antigen that stimulates an adaptive immune response is handled by a small number of B-cells, each producing antibodies of different affinity. Storing high affinity antibody producing cells from the first infection in order to form a large initial specific B-cell sub-population for subsequent encounters considerably enhances the effectiveness of the immune response to secondary encounters.

In Figure 3.3 an immune response (memory) with infection of two antigens in two phases is shown. The immune system first detects the Ag1's invasion, and after a lag phase, the antibodies against Ag1 will start increasing in concentration and affinity up to a certain level, and when the infection is eliminated, its concentration begins to decline. This first phase is known as the primary response. When another antigen Ag2 is coming, the same pattern of response will rise again with a kind of antibody different from the one that recognizes Ag1. The most important property of immune system is that the B-cells that adapt to a certain type of antigen Ag1 can present a faster and more efficient secondary response not only to Ag1 but also to any structurally related antigen of Ag1.
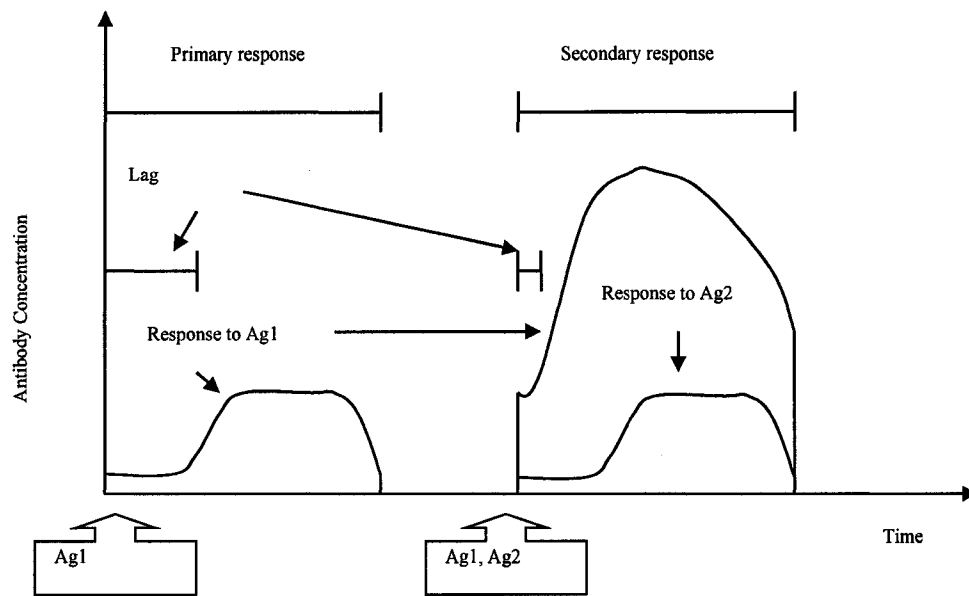
Figure 3.3: Primary and Secondary Responses

In comparison with the primary response, the secondary response is characterized by a shorter lag phase, a higher rate of antibody production and longer persistence of antibody synthesis. Moreover, a dose of antigen substantially lower than that required for initiating a primary response can cause a secondary response.

7. Affinity Maturation

In a T-cell dependent immune response, only high-affinity B-cells are selected into the pool of memory cells. During clone selection, random changes are introduced into the variable region genes and occasionally one such change will lead to an overall increase in the affinity of the antibodies. Antibodies present in a secondary response on an average have a higher affinity than those of the primary response. The increase in antibody affinity from the primary to the secondary response shows that the maturation of the immune response is a continuous process. Hence, there are four essential features of

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the adaptive immune response: 1) sufficient diversity to deal with a universe of antigens; 2) discrimination of self from none self; 3) adaptability of the antibodies to the selective antigens; 4) long lasting immunological memory.

The repertoire of antigen-activated B-cells is classified into two mechanisms: Hypermutation and receptor editing. These two mechanisms are discussed in the next chapter from a viewpoint related to information processing. The repertoire is not only diversified through a hypermutation process but mechanisms exist such that rare B-cells with high affinity mutant receptors can be selected to dominate the response. Due to the random nature of the somatic mutation process, large proportions of mutating genes become non-functional or possibly develop harmful anti-self specificities. These cells with low affinity or the self-reactive cells must be efficiently eliminated.

8. Summary

The immune system is a remarkable natural defence entity. In this chapter, a number of fundamental features and principles of immune system are presented, giving an outline of whole immune system structure and a brief introduction of its main components.

Moreover, the working methods of the immune system are explained by classifying it into two distinct but interacting mechanisms: the innate immunity and adaptive immunity. While the innate immune system focuses on the ability of immune system to extract molecular information via MHC molecules to be presented to T-cell, the adaptive immune system concentrates on the creation of B-cell antibodies against the infection. Through the process of adaptive immune response, it is clearly evident that

there are many interesting natural processes, such as learning and memory of immune system, clone selection principle and affinity maturation.

The immune system exhibits capabilities of learning, memory and adaptation. For these aforementioned reasons, it is not difficult to imagine the immune system as a mechanism of vast potential for applications in a variety of fields. Based on these exciting properties and advantages of the immune system, an artificial immune system that is able to extract valuable information using the properties of the immune system can be created for effective and powerful information processing systems. In the following chapter, a natural defence mechanism to develop a complete framework for the artificial immune algorithm is presented.

CHAPTER IV

ARTIFICIAL IMMUNE ALGORITHM

1. Background

In the past few decades, many computational intelligence methods such as neural network, evolutionary algorithm, annealing algorithm and artificial genetic algorithm have been well established. Very recently, the immune systems have aroused researcher's interest due to its mysterious mechanisms that makes it well suited for certain applications.

Although research and applications of the immune system is still in its infancy, the rich properties of the immune system provide researchers with a lot of promise. Besides, the mechanisms of immune system show that they can be applied in many fields, such as computation optimization and information processing.

There are several works in literature that introduce architecture models for artificial immune system, such as construction model [19], a formal model [20] and a physical model [21]. However, these works are usually either too restricted to a particular application or they do not embrace enough immune concepts or components to formulize a complementary framework of artificial immune system. In 2001, de Castro attempted to provide such a general-purpose framework on both theoretical immunology and artificial immune system in order to build a novel computational tool to solve complex problems. Some influential computational algorithms of immune principles, theories, and processes were viewed and brought together into a single framework.

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2. Artificial Immune system

In the previous chapter several mechanisms and main components of the natural immune system were introduced. The majority of immune theories have been almost entirely conceptual or non-mathematical in nature. The mathematical analysis of immune phenomena is extremely important to the science of immunology. This can be achieved through physical modeling, writing a special purpose computer program or by using a general simulation package. Mathematical analysis and models are applied to the immune phenomena through several steps: 1) Through modeling and identification theory, it is possible to provide a deeper and more quantitative description of the immune system and its corresponding experimental results; 2) adopt critical analysis of hypotheses to understand the biological mechanisms; 3) assist in the prediction of behaviours and the design of experiments; 4) stimulate new and more satisfactory approaches to vaccination policies, treatment of diseases and control of graft and transplant rejections; and 5) allow the recovery of information from experiment results.

Based on these steps, an experiment can be operated in a controlled environment for the purpose of gathering observations, data or facts, demonstrating known facts or theories and testing hypotheses or theories. We can also evaluate the performance of hypotheses or theories by comparing experimental results with their predictions. Artificial immune systems are intelligent methodologies inspired by the immune system towards a real world problem solving.

Artificial immune systems are data manipulation, classification, representation and reasoning methodologies which follow a biologically plausible paradigm. Therefore, for a system to be characterized as an artificial immune system it has to embody some fundamental features; 1) a basic model of an immune component (e.g. Cells, molecules

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and organs); 2) incorporate ideas or principles from theoretical and/or experimental immunology; and 3) aim at problem solving [22].

3. A framework for Engineering AIS

The first step to build a framework for artificial immune system is to devise a set of models for the components of natural system. In order to establish the engineering artificial immune system, some clues are found by glancing at other soft computing approaches inspired by biology, e.g. Artificial Neural Network (ANN). A set of artificial neurons can be arranged together so as to form an artificial neural network. A framework to design an ANN is composed of a set of artificial neurons, a pattern of interconnection for these neurons and a learning algorithm. Therefore, a similar framework to design artificial immune system can be proposed in a similar manner: a representation to create abstract models of immune organs, cells and molecules; a set of functions termed affinity functions, to qualify the interactions of these artificial elements and a set of general purpose algorithms to govern the dynamics of the artificial immune system.

During the building of abstract models of immune cells, molecules and their interactions, it is important to bear in mind the assumption that an antibody corresponds to the portion of any leukocyte capable of recognizing a molecule pattern and an antigen is equivalent to any pattern that can be recognized by this antibody. The strength of binding between an antigen and an antibody is termed their affinity or degree of match.

The concept of shape space is introduced to quantitatively describe the interactions between molecules of the immune system and antigens. It is assumed that it is possible to adequately describe the generalized shape of an antibody by a set of L

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parameters (e.g., the length, width, and the height of any bump or groove in the combining site, its charge, etc.). Therefore a point in an L-dimensional space, called shape space S specifies the generalized shape of an antigen binding region of the molecular receptors on the surface of immune cells with regard to its antigen binding properties. Also, it is assumed that a set of L parameters are used to describe an antigenic determinant, though antigens and antibodies do not necessarily have to be of the same length. The mapping from the parameters to their real biological counterparts is not important from a computational standpoint but will be basically dictated by the application domain of the artificial immune system.

Mathematically, the generalized shape of any molecule 'm' in a shape space S can be represented as an attribute string (set of coordinates) of length L. Thus, an attribute string $m = <m_1, m_2, \cdots, m_L>$ can be regarded as a point in an L-dimensional shape space, $m \in S^L$. This string is usually driven by the problem domain of the artificial immune system and will be important in the definition of which measure will be used to quantify their interactions. Most importantly, the type of attribute will define the type of shape space to be adopted as follows: 1）Real valued shape space: the attribute strings are real valued vectors; 2) Integer shape space: the attribute strings are composed of integer values; 3) Hamming shape space: composed of attribute strings built out of a finite alphabet of length k.

The affinity between an antibody and an antigen involves several processes, such as short range interactions based on electrostatic charge and hydrogen binding. In order for an antigen to be recognized, both antigen and antibody must bind complementary with each other over an appreciable portion of their surfaces. The shape and charge

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distributions can be considered as properties of antigens and antibodies that are important to determine their interactions.

Without loss of generality, an antibody molecule is represented by the set of coordinates $Ab = <Ab_1, Ab_2, \cdots, Ab_L>$ and an antigen is $Ag = <Ag_1, Ag_2, \cdots, Ag_L>$. The interaction of antibodies or of an antibody and an antigen is evaluated via a distance measure termed as affinity measure between their corresponding attribute strings. The affinity measure performs a mapping from the interaction between two attribute strings into a nonnegative real number that corresponds to their affinity or degree of match. Given an attribute string representation of antigen and a set of antibodies, for each attribute string of an antibody molecule, one can associate a corresponding affinity with the given antigen. Thus, an affinity landscape can be defined on the shape space, as illustrated in Figure 4.1.

According to the distance measure used to evaluate the affinity between the components of the artificial immune system, the affinity D between an antigen and an antibody in the shape space is calculated.

$$D = dis\|Ab_i - Ag_i\|$$

The common shape spaces are real valued space, including Euclidean and Manhattan. An alternative to real valued shape spaces is the Hamming shape space. Equation 1 depicts the Hamming distance measure used to evaluate the affinity between two attribute strings of length L in a Hamming shape space.
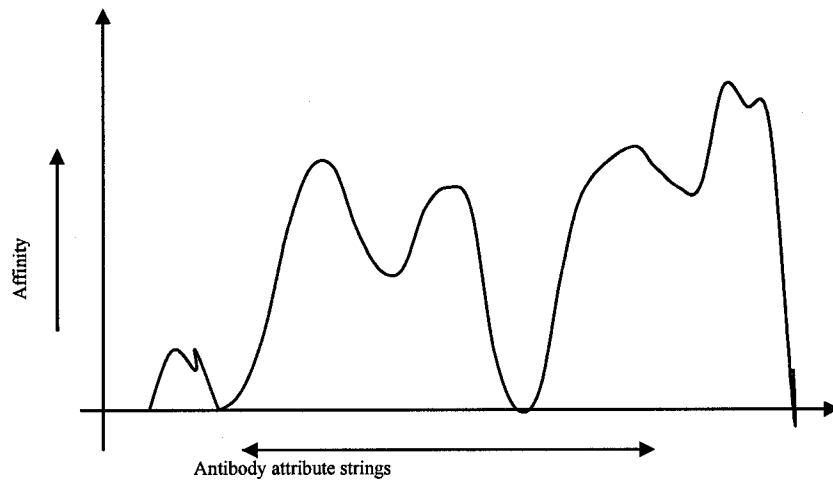
Figure 4. 1: Antibodies Affinity Landscape

5. Main immune mechanism principles

The immune system is a complex of cells, molecules and organs with the primary role of limiting damage to the host organism by pathogens (called antigens, Ag), which elicit an immune response.

In the normal course of the immune system evolution, the strength and specificity of the Ag-Ab interaction is measured by the affinity of their match [23]. The initial exposure to an Ag that stimulates an adaptive immune response is handled by a small number of low-affinity B cells. The effectiveness of the immune response to secondary encounters is enhanced considerably by the presence of memory cells associated with the first infection, capable of producing high-affinity Ab's after subsequent encounters. From this procedure it can be stated that learning in immune system involves raising the population size and the affinities of lymphocytes (B cells) that have proved themselves to

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be valuable during the antigen recognition phase. Thus, the immune repertoire is raised from a random base to a repertoire that more clearly reflects the actual antigenic environment.

An important principle which is meaningful from engineering point of view is clone selection. The main concepts of this principle were introduced in the previous chapter and here the focus is to extend this principle into a mathematical or engineering model. Given a set of patterns to be recognized(S), the basic steps of the clone principle are : 1) Initialization: create an initial random population of individuals (P); 2) Antigenic presentation: for each antigenic pattern, do affinity evaluation, clone selection and expansion, affinity maturation and Metadynamics; 3) repeat above step 2 until a certain stopping criterion is met.
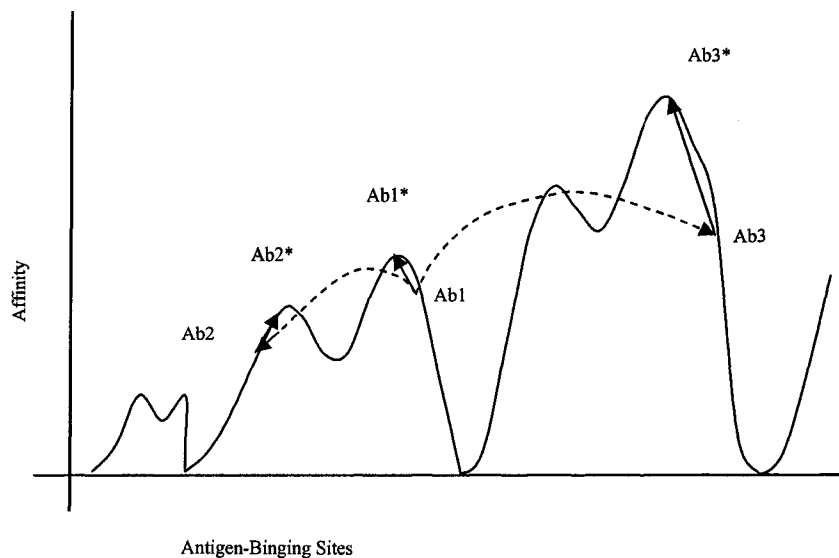
Figure 4. 2: Schematic Representation of the Shape Space for an Affinity Landscape

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Moreover, in a T-cell dependent immune response, the repertoire of Ag-activated B cells is diversified basically by two mechanisms: hypermutation and receptor editing [24], they are used to introduce diversity during an immune response. Receptor editing offers the ability to escape from local optima in an affinity landscape. Figure 4.2 illustrates this idea by considering all possible Ag-binding sites depicted in the horizon axis, with the most similar ones being adjacent to each other. The Ag-Ab affinity is shown on the vertical axis. If a particular Ab (Ab1) is selected during a primary response, then point mutations allow the immune system to explore local areas around Ab1 by making small increments toward an Ab with higher affinity, leading to a local optima (Ab1*). Since mutations with lower affinity are lost, the Ab's tend to go up the hill. Receptor editing allows an Ab to take large steps through the landscape, landing in a locale where the affinity might be lower (Ab2). However, occasionally the leap will lead to an Ab on the side of a hill where the climbing regions is more promising (Ab3), reaching the global optimum. From this locale, point mutations can drive the Ab to the top of the hill (Ab3*). To conclude, point mutations are good exploring local regions, while editing may rescue immune responses stuck on unsatisfactory local optima.

6. Algorithm and Processes

Given a suitable representation for the immune cells and interactions, it is possible to present an artificial immune algorithm that models specific aspects of adaptive immune system. Based on the immune concept, together with the affinity maturation process it can be demonstrated that these biological principles can lead to the development of useful computational algorithms. The algorithm presented focuses on a

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systemic view of the immune system and does not take into account cell-cell interactions. The scope of this thesis is not to model exactly any biological phenomenon, rather to show some basic immune principles that can help us better understand the immune system and to solve complex engineering tasks. The main features of the immune algorithm imitate immune system with following aspects:

1)   Proliferation and differentiation on stimulation of cells with Ag's;

2)   Generation of new random genetic changes expressed subsequently as diverse Ab An important principle which is meaningful from engineering point of view is patterns using a form of accelerated somatic mutation (affinity maturation);

3)   Estimation of new differentiated lymphocytes that carry low affinity antigenic receptors.

After presenting the immune system theory briefly, an algorithm is developed and implemented as follows: 1) maintenance of a specific memory set; 2) Selection and cloning of the most stimulated Ab's; 3) Elimination the non active Ab's 4) affinity sort and Ab's diversity; 5) reselection of the Ab's proportionally to their affinity.

In addition to somatic hypermutation and receptor editing, a fraction of new cells from the bone marrow are added to the lymphocyte pool in order to maintain the diversity of the population. Then under an engineering perspective, the cells with higher affinity are preserved as high-quality candidate solutions and are only replaced by improved candidates, based on statistical evidences. Thus, a specific memory set as part of the whole repertoire for imitating this feature in immune system is maintained.

A shape-space model that aims at quantitatively describing the interactions among Ag's and Ab's is defined. The set of features that characterize a molecule is called its

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generalized shape. The Ag-Ab codification determines its spatial representation and a distance measure is used to calculate the degree of interaction between these molecules. Mathematically, the generalized shape of a molecule (m), either an Ab or Ag, can be represented by a set of L attributes directly associated with coordinated axes such that m can be regarded as a point in an L-dimensional real-valued shape space. The length and cell representation depends upon each problem and is described later.

The main procedure of the algorithm is depicted as follows (Figure 4.2):

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

2) Determine the n best individuals, Pn, 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 affinity of the antibody. A maturated antibody population is generated (C*);

5) Based on C*, select a% of the highest affinity cells to imitate the new marrow cells by producing C**

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

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7) Replace some (d) low affinity antibodies of the population, maintaining its diversity.

In our implementation, it was assumed that the **n** highest affinity Ab's were sorted in ascending order after step 3, so that the number of clones generated for all these **n** selected antibodies was given by

$$Nc = \sum_{i=1}^{n} round(\frac{\beta \bullet N}{i})$$

Where Nc is the total number of clones generated for each of the Ag's, β is a multiplying factor, N is the total number of Ab's, and round(.) is the operator that rounds its argument towards the closest integer.

Nd → Pr / M (1)

(7)

(6)

Select (2)

Pn

Re-Select

Clone (3)

C** C

(5)

C* Mature

(4)
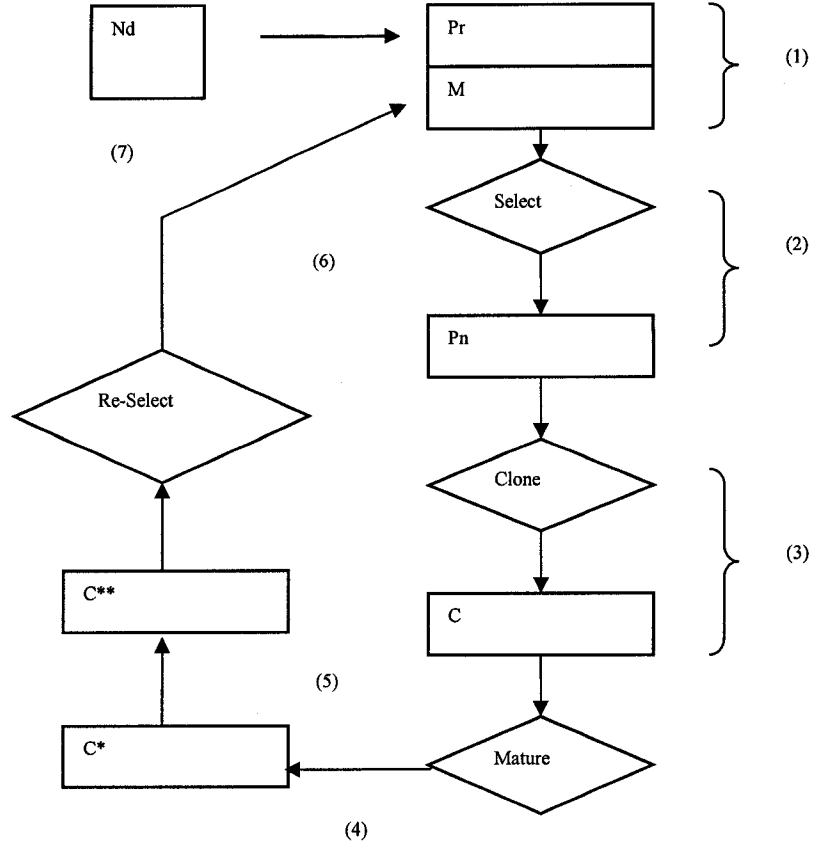
Figure 4. 3: Main Blocks of the Algorithm

The affinity measure takes into account the Hamming distance (D) between an antigen Ag and an antibody Ab, according to

$$D = \sum_{i=1}^{L} \delta_i, \quad where \quad \delta_i = \begin{cases} 1, & if \quad Ab_{ki} \neq Ag_{ji} \\ 0, & otherwise \end{cases}$$

The pseudo code for the immune algorithm as follows:

Input: P, N, n, d, L,

Output: Ab, f

For t=1 to N,

F   :=decode (P);   % step2

Pn   :=select (P, f,n)   % step3

C   :=clone(Pn, β,f);   % step4

C*   :=hypermut (C,f)   % step5

C**:=select(C*, f*,n)   % step 6

d :=generated (d,L)   % step 7

P   := replace (P, d, f);

End;

Note: function decode is supposed to decode P and evaluate the affinities for these decoded values.

7. Summary

Artificial immune system can be defined as a computational system inspired by theoretical immunology and observed immune functions, principles and models that are applied to problem solving. It is possible to apply these basic concepts into engineering field, such as information processing and intelligence calculation.

According to current research result of immune system, the focus is on several important mechanisms which can feasibly be implemented in applications such as clone selection principle, hypermutation and receptor editing. Utilizing these immune

metaphors, an artificial immune algorithm is implemented in a methodical and rigorous fashion. Thus, simple abstract models of basic immune components and processes have been drawn together into a single framework for the construction of artificial immune algorithm which could be adjusted for different application environment.

CHAPTER V

APPLICATION CASES IN MULTIPLE SENSOR NETWORK

1. Image registration

Multiple sensor systems receive information of target with different positions and orientations. These kinds of information need to be merged in a common combination system by some methods, such as image registration, in order to provide a detail picture of target. Image registration refers to the fact that any two-dimensional sensor reading can be represented as an image and the task is to find the correct mapping of one image onto another. Given two overlapped sensor readings, we hope to find the position and orientation of the sensor2 relative to the sensor1. F is a function that maps a reading of sensor2 to that of sensor1. Considering S1 and S2 represented by vector like $(x_1, x_2, x_{3,} ..., x_n)$, F implements S2 to S1 as equation 1 in case of free of noise conditions.

$$F (S2) = S1 \qquad (1)$$

In other words, in order to fuse multiple sensor readings, they must be registered into a common coordinate system. This problem was originally posed in [25]: Two sensors with identical geometric characteristics return readings from the same environment. The goal is to find the optimal parameters (X_t Y_t θ) to define the relative position and orientation of sensor2 onto the sensor1. The search space is a three-dimensional vector space and the transformation can be presented as equation 2 and shown in Figure 5.1.

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta & Xt \\ \sin\theta & \cos\theta & Yt \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \qquad (2)$$

However, in the real world, all the sensor readings inevitably contain noise; here, we consider this noise as Gaussian distribution so as to modify fitness function in equation1 by equation 3:

$$\sum \left(read_1(x,y) - read_2(x',y') \right)^2 / \left(K(W) \right)^2 \qquad (3)$$

K (W) is the number of pixels in the overlap for W in the search space.

In this problem, the fitness function is composed of stochastic noise and a unique minimum that refers to overlap of grey-scale values in two images.
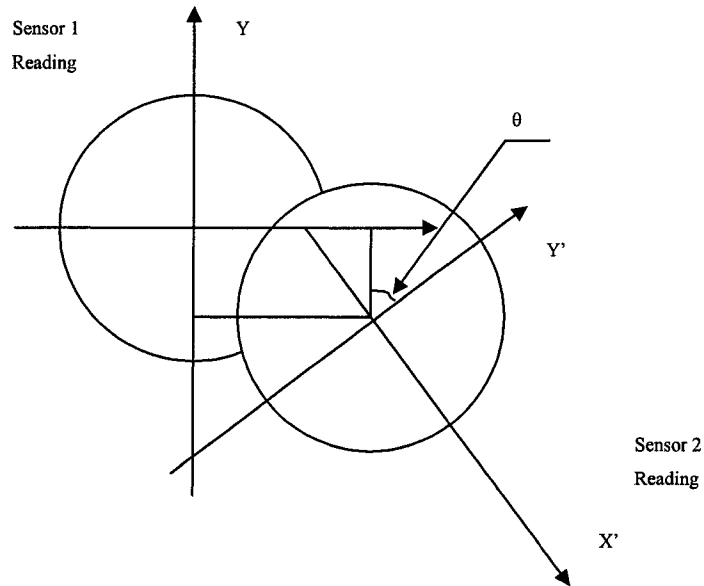
Figure 5.1: Two Sensor readings

Therefore, we seek the values of X_t, Y_t and θ that provide the globally minimal solution for equation 3 [26].

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2. Configuration of sensor system

Multi-sensor system is a redundant system that achieves fault tolerance by duplication of components. It increases the ability of systems to interact with their environment by combining independent sensor readings into logical representations. Sensor integration of highly redundant systems offers these advantages: 1) Multiple inaccurate sensors can cost less than a few accurate sensors; 2) sensor reliability may increase; 3) sensor efficiency and performance can be enhanced; 4) self-calibration can be attained. But the feasibility of the system requires attention be paid to both reliability bounds and cost. Therefore, highly redundant sensors are used in key areas and their designs need a best possible trade-off at least cost. The proposed method focuses on the configuration of a sensor system to satisfy the system dependability with heterogeneous components at a lower cost model. Therefore, the problem that needs to be solved is: Given J type sensors, we have to find a module that has the least cost while fulfilling the requirement of system dependability. On the other side, a similar problem can also be proposed as given a cost limit for the system, how we can configure a sensor system with maximal reliability. From [27], a Markov chain model provides our process to evaluate the reliability of a sensor system. Assuming that the system contains N identical sensors, the sensor's failure is statistically independent. If each sensor has an identical probability of functioning r(t) (if a sensor has a constant failure rate λ, the reliability for that sensor $e^{-\lambda t}$) at a time t and a probability of being faulty q(t) when q(t)=1-r(t), the reliability for the whole system is the sum of the probabilities for the states with i equal to N to [N/2] +1. Hence, we obtain equation (4) for calculating the reliability of a system composed of two different types of components where N_1 (N_2) is the number of sensors of type 1 (2)

and $r_1(t)$ ($r_2(t)$) are the reliabilities of sensor type1 (2). This concept can be easily extended to applications dealing with multi-sensor systems.

$$R(t) = \sum_{k=0}^{N_1} \left[\binom{N_1}{k} r_1^k (1-r_1)^{N_1-k} \times \sum_{m=\frac{N}{2}+1-k}^{N_2} \left(\binom{N_2}{m} r_2^m (1-r_2)^{N_2-m} \right) \right] \qquad (4)$$

Obviously, the cost for whole system can be calculated with the equation below.

$$\sum_{i=0}^{j} C_i Q_i \qquad (5)$$

Here, Q_i refers to the number of type i sensors and C_i is the cost of each type i sensor.

It is a combinatorial optimization problem and cannot be solved by linear programming since the calculation procedure of system dependability is nonlinear. In [23], an example to show the features of this problem is given. The jaggedness on the shape of the search space found by using an exhaustive search algorithm indicates that the search space has many local minima. The search methods that depend only on information in the neighbourhoods of a point will be unsuitable for solving this problem. Although the Genetic Algorithm (GA) and Simulated Annealing (SA) obtain good results for this problem, the immune algorithm shows a better result than the genetic algorithm for a problem having many local optima [28].

3. Multiple fault tolerance design

The potential advantages of multi-sensor system are redundancy, complementarities, timeliness and cost of the information. It increases the ability of sensors to interact with its environment by combining independent sensors into a logical network that is capable of self-test and calibration, while enhancing its overall reliability,

efficiency and performance. Imperfect tests introduce additional elements of uncertainty into the diagnostic process: the past outcome of a test does not guarantee the integrity of components under test or a failed test outcome does not mean that one or more of the implicated components are faulty. Thus, the diagnostic procedures must hedge against this uncertainty in test outcomes and we have to take system testability into consideration during the design phase of the system configuration.

During the configuration of a multiple sensor system, sensor planning in the design phase to obtain maximum fault isolation for a given cost is extremely important. Feasibility requires attention be paid to both fault diagnostic bounds and cost. In other words, success in designing the redundant sensor systems depends on making the best possible trade-off between cost and fault diagnosis.

Using a system model, the system dynamics, reliability of data, fault probabilities and effects of faults on observable system parameters are evaluated. The fault effect information is translated into cause-effect dependencies between the faults and possible effects, and the corresponding false alarm and detection probabilities are computed.

We use a two-layer system to model a sensor system as shown in [29]. A bipartite graph model is used to display the structure representing a given problem. The top layer refers to a failure source that belongs to the set of failure sources. The bottom layer represents the discrepancy caused by each sensor on different periods.
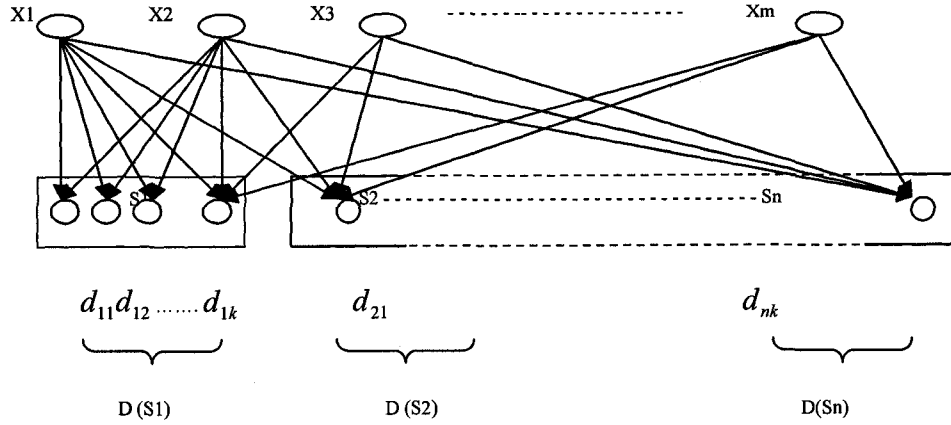
Figure 5.2: Two-Layer Sensor System Model

In order to establish our model, we define the corresponding parameters for a sensor system as shown in figure 5.2.

- First, a finite set of available sensors.

- Second, a finite set of binary discrepancies D (S).

$$D(S) = \{d_{jk}\}(j = 1 : n, k = 1 : m)$$

Here, D (S) means the complete set of observable discrepancies in the sensor system, while d_{jk} refers to k^{th} the discrepancy from the j^{th} sensor.

- Third, the failure sources set is x and associated with the priori probabilities p (x).

- Finally, the set of edges E=$\{e_{ijk}\}$ specifies the functional information flow between the set of failure sources and observable discrepancies in the system while $P_{ijk} = (Pd_{ijk}, Pf_{ijk})$ represents the detection and false-alarm probabilities associated with failure source i and observable discrepancy d_{jk}.

The focus is on configuring a sensor system with maximizing diagnostic ability as

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$$\underset{s \subseteq S}{mas} \Pr(X|D(S)) \qquad X = \{X_t\}$$

$$C_{\text{limited}} \le C(S)$$

D (S) is the set of discrepancies observed in the sensor system and represents a potential fault subset that comprises one or more failure sources and belongs to set X. Theoretically, the power set of subsets of X has cardinality . In practice, many subsets have very low probabilities of occurrence and are not considered in the design procedure. $C(S)$ refer to the constraints imposed on the solution with respect to the different sensor attributes, such as cost, weight, power consumption, volume and the permissible limits of variance for each attribute. Upon the assumption that failure sources are independent, a priori probability associated with a potential fault subset can be evaluated as:

$$\Pr(X_t) = \prod_{i=1}^{m} p(x_i)^{I_i} (1 - p(x))^{1-I_i} \qquad \text{Where} \quad I_t = \begin{cases} 1 & x_i \in X_t \\ 0 & otherwise \end{cases}$$

In this sensor system model, we construct a relationship between failure sources and sensor discrepancies and configure a sensor network with maximal diagnosis ability. In other words, the problem concerns the multiple fault diagnosis for the most likely candidate fault subset that best explains the set of observed discrepancies [30]. Through this process, we can find the importance of each sensor and evaluate a set of sensors in a fault detection system. In order to fulfill our goal, we use a series of processing to design a sensor system as shown in Figure 5.3.

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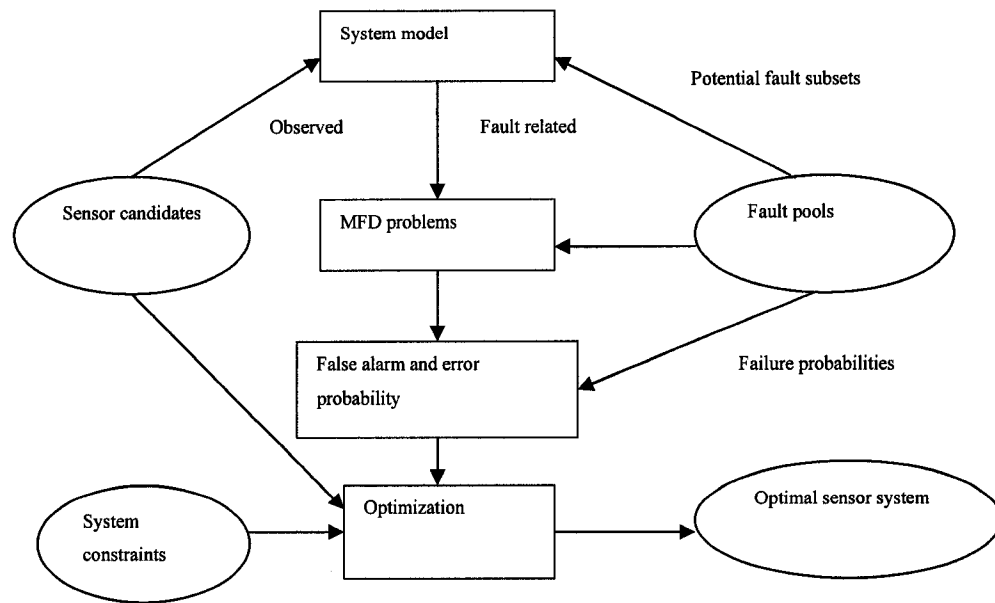
Figure 5.3: Sensor System Design Process

For a potential fault subset X_t, we record the corresponding discrepancy in the sensor system model and also compute the potential fault subset probabilities $(P(X_t))$. For each subset of these discrepancies, the algorithm decides on the most probable potential fault X_t^c which was related to a set of discrepancies caused by sensor subsets s, $s \in S$. Finally, we can get the results of all the subsets of X and evaluate the diagnostic merits of those sensor subsets.

We can use the subsets of discrepancies caused by a potential fault subset X_t and compute the next three performance measures for evaluating the merits of sensor subsets:

1) Probability of correct diagnostic decision (P_d)

2) Probability of false diagnostic decision (P_f)

3) Probability of total error (Pe)

Here, P_d refers to the fraction of correctly diagnosed faults among those actually present while P_f means the fraction of falsely diagnosed faults from among those are not present relative to the reference diagnoses. P_e is the average Hamming distance between the obtained diagnosis and the reference diagnosis over the entire potential fault subsets. The performance of each sensor is obtained as follows:

$$P_{dj} = \frac{1}{N_j} \sum_{i=1}^{N_j} \frac{\left| X_{tji}^c \bigcap X_{tji} \right|}{\left| X_{tji} \right|}$$

$$P_{fj} = \frac{1}{N_j} \sum_{i=1}^{N_j} \frac{\left| X_{tji}^c \bigcap X_{tji}^a \right|}{\left| X_{tji} \right|}$$

$$P_{ej} = \frac{1}{N_j} \sum_{i=1}^{N_j} \frac{\left| X_{tji}^c \bigcap X_{tji}^a \right| + \left| X_{tji} \bigcap X_{tji}^{ca} \right|}{\left| X_{tji} \right|}$$

N_j: Number of simulations.

X_{tji}: The set of target fault subsets used in the i^{th} run of the simulation.

X_{tji}^c: The set of diagnostic decisions obtained from algorithm in that run.

X_{tji}^a: The set of faults does not appear in the reference diagnosis.

Once we obtain the above performance data, we can configure the sensor system optimally by following equation:

$$\max \sum_{i=1}^{j} P_{di} S_i \quad \text{Once} \quad \sum_{i=1}^{j} C_i S_i \le C_{\text{limited}}$$

CHAPTER VI

EXPERIMENTS AND RESULTS

1. Image registration

The model used to represent the terrain in this thesis has several periodic elements combined with non-periodic elements. The equation to represent such a terrain is shown below:

$$f(x,y)=100+\frac{1}{100}\left(\begin{array}{l} -40x+45y-0.003xy+ \\ 0.002x^2-0.001y^2-20y\sin\left(\frac{x}{18}\right)+ \\ 35y\cos\left(\frac{y}{29}\right)-35\sin\left(\frac{x}{4}-\frac{y}{12}\right)+ \\ 12x\cos\left(\frac{xy}{100}\right) \end{array}\right) \qquad (6)$$

This model has been chosen since it inherits two characteristics that are necessary for the problem to be solvable but not trivial. The non-periodic elements ensure that there is a unique best match for the two sensors, whereas the periodic elements in the model ensure that this match is not obvious. Therefore an algorithm that searches for the best match should be capable of dealing with local minima within the search space.

Table 6.2 and Table 6.4 show the result of our experiments on one and three dimensions. All Abs on the search area converge at a global optimum i.e. minimum in Figure 6.1. Also from Table 6.5 and Table 6.6, it can be easily inferred that the immune algorithm is able to find optimal solution in presence of large amount of noise.

Table 6.1: Two Sensors' Location (1-D)

Sensor 1			Sensor 2		
X	Y	θ	X	Y	θ
128	128	0	128	128	2.8457
Noise level: 0					

Table 6.2: Result on One Dimension

ITERATIONS	Current θ	Current error
1	1.8911	-34.33%
10	2.7811	-2.27%
20	2.7980	-1.67%
30	2.8209	-0.87%
40	2.8422	-0.12%
45	2.8429	-0.1%

Table 6.3: Two Sensor's Location (3-D)

Sensor 1			Sensor 2		
X	Y	θ	X	Y	θ
0	0	0	91	91	2.7489
Noise level: 0					

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Table 6.4: Result on Three Dimensions

ITERATIONS	Current θ	X value	Y value
1	5.2499	15	7
15	2.6611	88	87
30	2.7301	90	87
45	2.7391	90	87
60	2.7413	90	91
75	2.7425	90	91
90	2.7430	91	91
100	2.7435	91	91
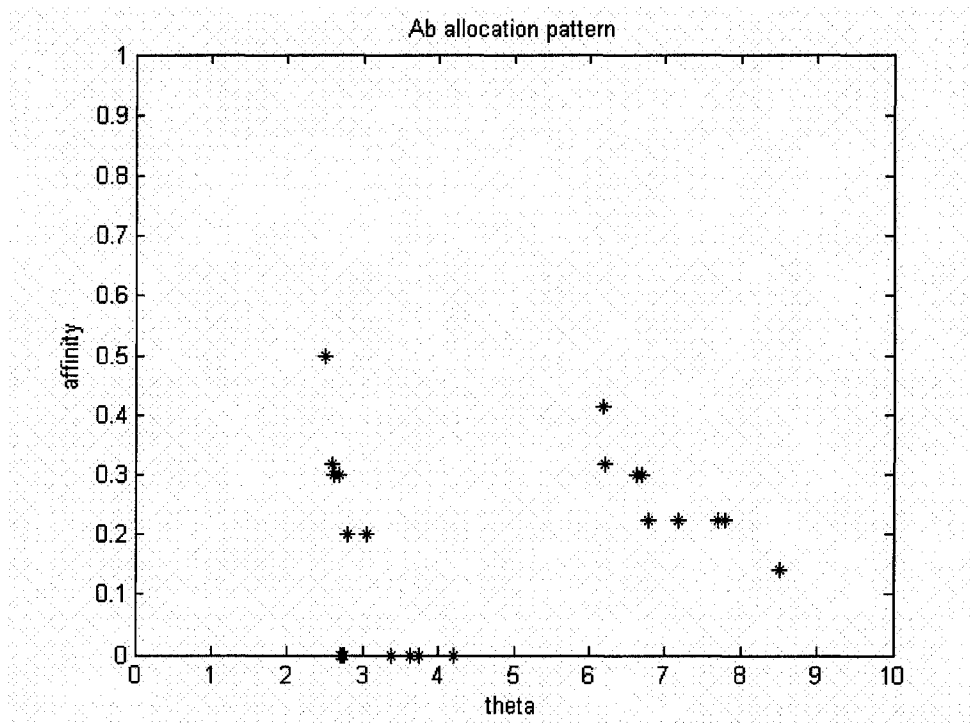
Figure 6.1: Ab's Allocation pattern During Search of Global Optima

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Table 6.5: Results in presence of Noise by AIS

Noise	Current θ	X value	Y value
0	2.7435	91	91
10	2.7445	91	90
20	2.7300	91	91
30	2.7381	91	89
50	2.7433	85	87
70	2.7631	92	85
90	2.7012	78	84

Table 6.6: Results by Genetic Algorithm

Noise	Current θ	X value	Y value
0	2.7474	89	91
10	0	92	92
20	2.7474	91	91
30	2.7474	89	89
50	2.7977	86	-18
70	6.0214	-48	6
90	1.2329	0	5

2. Minimizing cost

In this thesis, the immune algorithm is used to solve the problem proposed in [31] and to test its feasibility on various kinds of applications. Besides, we can also compare its result with genetic algorithms and simulated annealing.

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Table 6.7 shows the results of these algorithms. The immune algorithm succeeded in finding the global minimum like SA while GA failed to reach the global optima. Although SA found the global minimum in this case, it does not guarantee a globally optimal answer for different problems.

As mentioned earlier, we can also configure a redundant sensor system with limited cost to reach maximal system reliability by integrating several different types of sensors. The proposed algorithm achieved ideal results as shown in Table 6.8.

Table 6.7: Minimum Cost under Reliability Constraint

MINIMUM COST: 85.40 AVAILABILITY CONSTRAINT: 99.5%								
Iterations	S.1	S.2	S.3	S. 4	S.5	S. 6	S.7	S. 8	COST($)
1	1	0	2	0	2	0	0	2	95.76
20	0	0	0	0	2	0	2	3	95.30
40	2	1	0	1	0	0	0	1	94.22
60	2	1	0	0	1	0	0	1	93.72
80	1	1	0	0	0	0	1	2	92.76
100	1	1	0	0	0	0	0	3	92.36
120	0	1	0	0	0	0	0	4	85.40

Table 6.8: Maxima Reliability under Budget

Budget: 58 Dollars											
	S. 1	S. 2	S.3	S. 4	S. 5	S. 6	S. 7	S. 8	S.9	S.10	S.11	Dependability
Failure rate	0.06	0.15	0.13	0.5	0.11	0.32	0.07	0.22	0.01	0.19	0.22	
Repair rate	0.3	0.3	0.81	0.95	0.9	0.84	0.1	0.59	0.07	0.35	0.4	
Unit cost	$20.00	$10.00	$20.00	$5.00	$25.00	$15.00	$7.00	$8.00	$20.70	$6.80	$7.00	
SA config	0	0	0	0	2	0	0	1	0	0	0	94%
SA cost	$58											
GA config	0	0	0	0	1	0	0	1	1	0	0	93%
GA cost	$53.70											
IM config	0	0	0	0	2	0	0	1	0	0	0	94%
IM cost	$58											

3. Multiple fault endurance tolerance design

We implemented our algorithm on two available sensor systems to test its performance with respect to different sensor schemes.

Example A:

In this example, the candidate system comprises of seven possible sensors and each sensor reports one discrepancy. There are five failure sources and each sensor has a single attribute. The detection probability parameters are listed in Table 6.10 and it is assumed that the false alarm probabilities are zero. The costs related to each sensor are listed in Table 6.11 and values of P_{dj} and P_{ej} are shown in Table 6.9.

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If we set the configuration budget as 1300 and system permissible probability of error as 0.026, we found that the optimal sensor system is composed of five chosen sensors as in Table 6.11.

Table 6.9: Prior Probabilities (A)

	j=1	j=2	j=3	j=4	j=5	j=6	j=7
P_{dj}	0.83	0.79	0.77	0.78	0.81	0.73	0.8
$P_{ej}(10^{-3})$	2.9	4.3	3.4	6.7	3.6	4.8	5.1

Table 6.10: Sensors Prior Probabilities (A)

	i=1	i=2	i=3	i=4	i=5
J=1,k=1	0.06	0	0.68	0	0.1
j=2,k=1	0	0.81	0.09	0.85	0
J=3,k=1	0.54	0	0	0.45	0.9
J=4,k=1	0.74	0	0	0.52	0
J=5,k=1	0	0.72	0	0	0.18
J=6,k=1	0.06	0	0.68	0	0.1
J=7,k=1	0	0.81	0.09	0.85	0

Table 6.11: Designed Configuration for System A

	S1	S2	S3	S4	S5	S6	S7
P (x)	0.12	0.135	0.18	0.075	0.03	0.14	0.05
Cost	200	300	400	250	150	300	350
$C_{limited}$	1300						
$P_{elimited}$	0.026						
Solution	1	1	0	1	1	0	1
Total cost	1250						

We have also verified results by comparing P_d of obtained sensor configurations and original sensor schemes as mentioned earlier. From the Figure 6.2, we can see that

the sensor system designed maintains higher fault detection ability while saving the whole system cost.

Example B:

In this example, the candidate system comprises of ten possible sensors and each sensor reports two discrepancies. There are eight failure sources and each sensor has two attributes. The detection probabilities are listed in Table6.13 and values of and are shown in Table 6.12.

Table 6.12: Prior Probabilities (B)

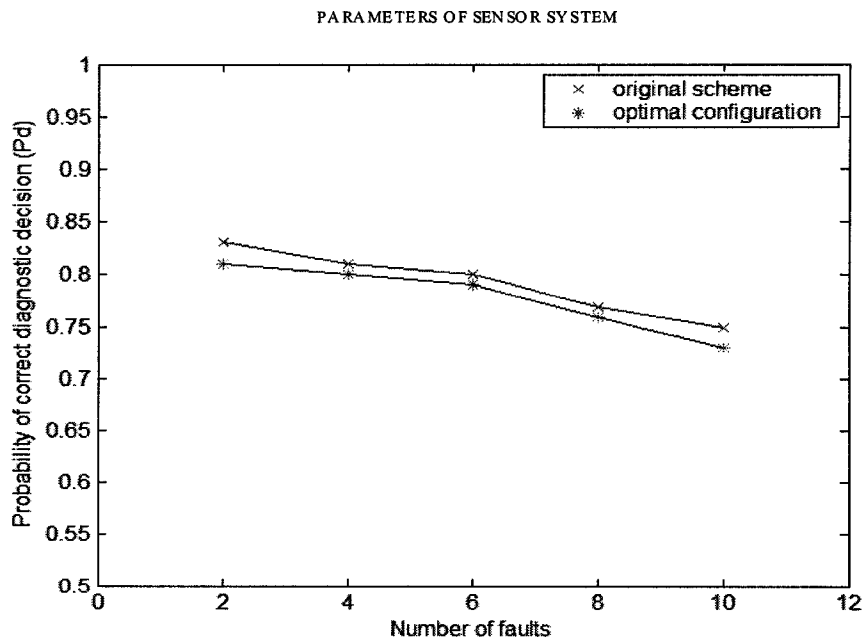|	$I=1$	$I=2$	$I=3$	$I=4$	$I=5$	$I=6$	$I=7$	$I=8$	$I=9$	$I=10$
P_{dj}	0.78	0.84	0.75	0.79	0.82	0.73	0.71	0.82	0.86	0.7
$P_{ej}(10^{-3})$	4.6	2.3	5.8	4.6	3.6	6.7	6.9	3.8	2.3	6.8

PARAMETERS OF SENSOR SYSTEM

Figure 6.2: Probability of Correct diagnostic decision and Faults 1

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Table 6.13: Sensors Prior Probabilities (B)

	l=1	l=2	l=3	l=4
J=1,k=1	0	0	0.6591	0.9457
j=1,k=2	0.2589	0.81	0	0.3876
J=2,k=1	0.3491	0	0.7734	0
J=2,k=2	0	0.5287	0.9143	0
J=3,k=1	0	0.119	0.2190	0.8712
J=3,k=2	0.6143	0	0.4356	0.6615
J=4,k=1	0	03159	0	0
J=4,k=2	0	0	0	0.2067

Table 6.14: Designed Configuration for Sensor system B

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
P(x)	0.184	0.452	0.128	0.605	0.582	0.059	0.712	0.582	0.236	0.586
Cost1	660	140	440	260	700	610	520	170	450	410
Cost2	300	650	230	710	440	720	330	400	550	380
$C_{limited}$	3500 3600									
$P_{elimited}$	0.0025									
SOLUTION	1	1	1	0	1	0	1	1	1	1
Total cost	3490 3280									

It is assumed that the false alarm probabilities are all zero. In this case the planned system budget is 3500 and 3600 respectively and the controlled permissible probabilities of error are under 0.0025. We found that the optimal sensor system is composed with set as shown in Table 6.14. We subsequently compared the probabilities of correct diagnostic decision between original scheme and optimal configuration. In Figure 6.2 and Figure 6.3, we noticed that the two set of experimental data has only a small variance and that the

optimally configured sensor system can meet the system requirements while simplifying the system structure.
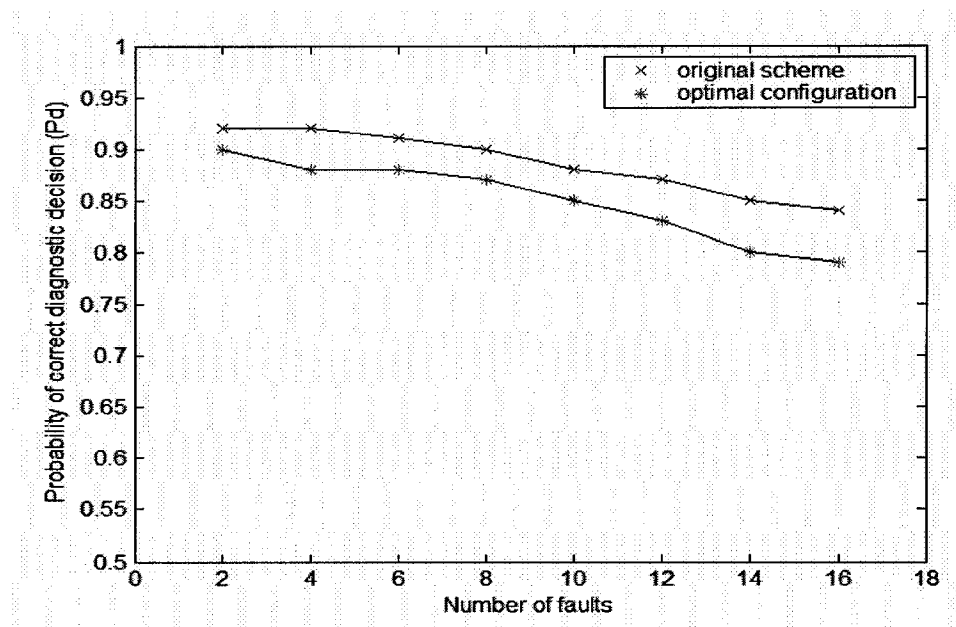

Figure 6.3: Probability of Correct diagnostic decision and Faults 2

CHAPTER VII

DISCUSSIONS AND CONCLUSIONS

1. Comparison with genetic algorithm

Through the use of biological systems as inspiration, artificial neural networks and genetic algorithm have been developed long ago compared to immune algorithm. As with the biological systems, it is possible to draw out several similarities and differences among their computational counterparts. This section is aimed at identifying the main characteristics of artificial immune algorithm according to the framework proposed in the previous section and comparing them with the GA. The comparison is done by identifying several features of each algorithm in a top to bottom fashion and their structures for possible characterization of the approaches.

A genetic algorithm can be defined as a stochastic algorithm whose search method tries to model the biological phenomena of genetic inheritance and natural selection. Simple genetic algorithms constitute abstract models of natural evolution and operate with a fixed size population and individuals represented by "genetic strings" of fixed length. New populations evolve through a probabilistic fitness selection of individuals that are capable of producing offspring's similar to parents via crossover and mutation. The main characteristics of a GA can be summarized as follows:

1) Population-based search;

2) The use of cost (fitness, objective or adaptability) functions instead of derivatives or other type of auxiliary knowledge

3) The use of probabilistic transition rules (selection and reproduction mechanisms) instead of deterministic.

A standard genetic algorithm can be described by the block diagram of Figure 7.1 and consists of several steps: 1) binary encoding; 2) reproduction and selection via Roulette Wheel; 3) single-point crossover; and 4) single-point mutation;

While immune algorithm introduced the concept of shape-space to quantitatively describe the interactions between molecules of the immune system and antigens that represent the problems and solutions separately. In the course of learning and evolution, the immune algorithm searches for the best possible solution in a given space. It is composed of the following steps: 1) random antibodies exposure to antigenic stimulus; 2) increase in size of specific antibodies sub-population (clones) or hypermutation; 3) affinity maturation of the antigenic receptor and 4) Clone selection and receptor editing.
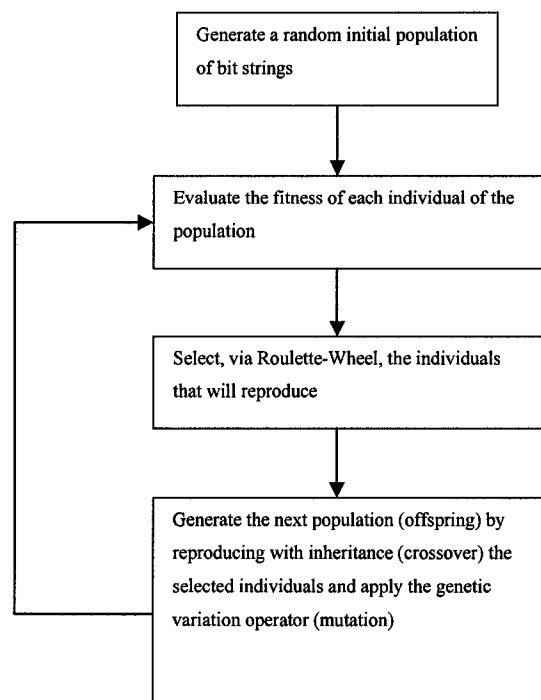

Figure 7. 1: Basic Genetic Algorithm Flowchart

Besides, if the search space is large and is not perfectly smooth, unimodal or known or if the fitness function is noisy, then the GA will have a good chance of being a

competitive approach. If the search space is smooth or unimodal, then gradient or hill climbing methods are much more superior to GA. If the search space is well understood such as a traveling salesman problem-TSP, heuristics can be introduced in specific methods, including the GA, such that they present good performance. The detail information can be found in many literatures and a basic flowchart of genetic algorithm is shown. Table 7.1 shows similarities and differences between GA and AIS in brief from an engineering point of view.

Table 7.1: Comparison of AIS with GA

	AIS	GA
Components	Attribute string in Antigen	Strings representing chromosomes
Structure	Set of discrete elements	Discrete chromosomes
Dynamics	Learning/Evolution	Evolution
Process	Clone Selection	Fitness proportional Selection
Mutation	Hypermuation without cross over	Point mutation, cross over
Selection Principle	Affinity maturation	Fitness of the chromosomes
Metadynamics	Elimination/recruitment of components	Elimination/recruitment of chromosomes
Interaction with other components	Through recognition of attribute strings	Through recombination operators/ fitness function
Threshold	Influences the affinity of elements	Influences genetic variation mechanisms
Non-linearity	Binding Function	Not explicit
Robustness	Population of components	Mainly affected by program initial status

2. Algorithm sensitivity

The artificial immune algorithm presented here adopts the natural immune response mechanisms of mutation, proliferation and receptor editing. Implementation of this algorithm on the problems of multiple sensor fusion shows that three parameters might determine the performance of the applied method such as convergence speed, the computational complexity and its capability to fulfill a multimodal search. The

parameters are: 1) n: number of Ab's to be selected for cloning giving rise to the population Abs; 2) N_c: Number of clones generated from best selected Abs; 3) d: Amount of low affinity Ab's to be replaced after each running of algorithm.

In order to make results clear and simplify our procedure, we test artificial immune algorithm on maximizing the function of $h(x) = \sin^4(5\pi x)$ to analyze its performance.

First, we set the parameters β=1, d=0 and test the relationship between n and convergence iterations to find the maxima of $h(x)$. Results show that the parameter n does not strongly influence the iterations or convergence speed. However, it heavily affects the number of antibodies to be cloned which may cause a higher computational cost to run the algorithm.

In order to evaluate the algorithm sensitivity in relation to parameter N_c, we set d=0 and both n and N are 10 while N_c is tested on values {5, 10, 15, 30, 40, 50, 60, 80, 120}. In this case, we consider convergence when the algorithm finds all peaks of function $h(x)$. Figure 7.2 clearly shows the trade-off between average iterations and N_c and indicates that the convergence speed increases when N_c increases. This result meets our expectations since larger number of N_c refers to larger number of available clones which accelerates the speed of convergence in terms of program iterations. The computational time per iteration also increases linearly with N_c.
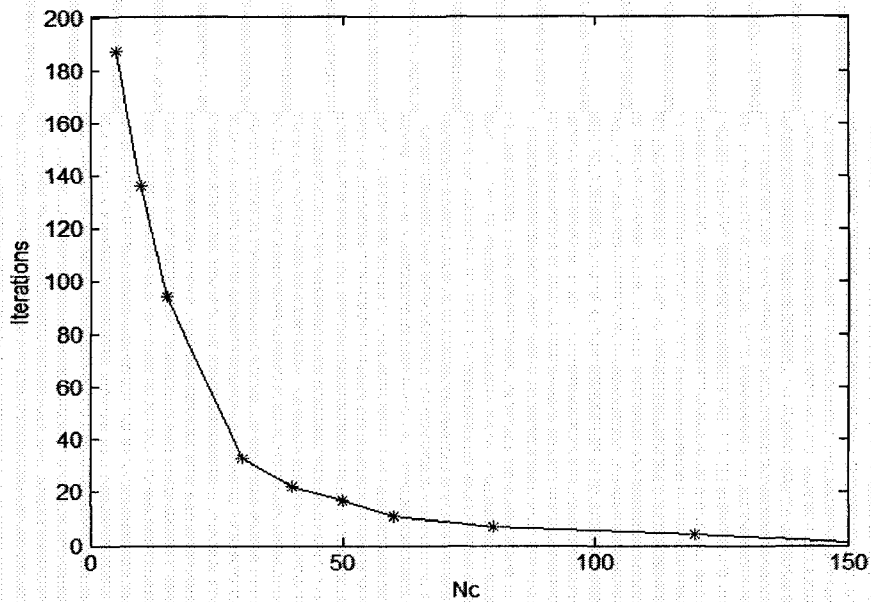
Figure 7. 2 : Iterations Effected by Nc

We also focus on the parameter d which refers to the number of low affinity antibodies to be replaced in each program loop. Most importantly it maintains the diversity of the population and makes it possible for the algorithm to explore new regions of the affinity landscape and imitate the mechanism of receptor editing. We set both **n** and **N** as 10 and observe the changes when d is 1, 2 and 5. From Figure 7.3, it is important to note that the algorithm is able to find all maxima when d is 1 and 2; corresponding to 10% and 20 % low affinity antibodies that have been replaced. We can also note that it finds three peaks when we set d =5 and runs the same iteration numbers as with d =1. It shows that a high value for parameter d causes a random search through the affinity space and may find all peaks eventually with more computational cost. Therefore we suggest setting d around 15% of the size of the antibodies from the viewpoint of saving computational complexity.
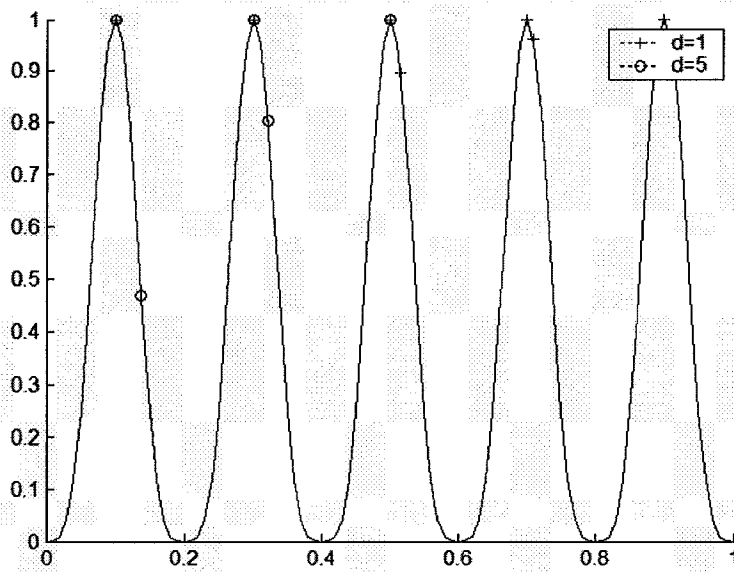
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Figure 7. 3: Optima Searching Comparison of Parameter *d*

3. Conclusion

In this thesis, we focus on application of a new method inspired by the human immune system on the problems of multiple sensor system. At first, we introduced the main concept of multiple sensor system and basic terminology. A model of multiple sensor networks was introduced along with a summary of applications, characteristics, and advantages. We also present the general processes to deal with the problem of multiple sensor fusion by giving a brief introduction to a number of tools and constructs needed for multiple sensor processing.

Later we introduced a number of fundamental features and principles of immune system, giving an outline of the whole immune system structure and a brief introduction of its main components. Several interesting mechanisms in adaptive immune response are

found useful from an engineering perspective. Based on this, we present the artificial immune algorithm for non-linear optimization problems of multiple sensor system.

Through the experiments, we also noticed that this evolutionary-like algorithm can be regarded as a cooperative and competitive algorithm since it performs its search through the mechanisms of somatic mutation and receptor editing, anxiously testing best solutions on the given search space. The hypermutation is responsible for exploring local regions, while receptor editing make big steps to search potential global optima. We obtained satisfactory results on given experiments both on image registration and configurations of the sensor networks.

Finally, we compared the artificial immune algorithm with a genetic algorithm theoretically to show its uniqueness. Essentially, their encoding schemes and evaluation functions are similar, but their evolutionary search processes differ from the viewpoint of inspiration, vocabulary and sequence of steps. Besides, we test the capacity of artificial immune algorithm on key aspects of an algorithm, such as convergence speed and computation complexity by observing the results caused by changes of some parameters. It can locate most of local optima compared to traditional algorithms. Therefore we show that the artificial immune algorithm is a novel method to provide solution for the problems of multiple sensor system and also for many nonlinear problems.

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