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A BIO-INSPIRED MULTI-AGENT CONTROL FRAMEWORK

H. Y. K. Lau V. W. K. Wong and A. W. Y. Ko

hyklau@hku.hk
Department of Industrial and Manufacturing Systems Engineering
The University of Hong Kong, Pokfulam Road, Hong Kong, PRC

Abstract: The biological world has often offered inspirations to novel approaches to solving engineering problems. This paper presents an engineering analogy of the human immune system, known as the artificial immune system (AIS) for the strategic control of multi-agent based systems such as fleet of autonomous guided vehicles or a multi-jointed manipulator. The human immune system is a complex, adaptive and highly distributed system that exhibits the behaviors of autonomy, self-organizing, distributivity, fault tolerance, robustness, learning and memory, which is underpinned by a set of theories including the immune discrimination and specificity theories. A distributed control framework is developed based on the conceptual framework of the immune system. The AIS-based multi-agent control paradigm is studied via two key mechanisms in the generalized control hierarchy, namely, detection of events and the activation of control actions. Simulation and experimental study using a fleet of autonomous guided vehicles in a material handling system to illustrate the effectiveness of the proposed framework. *Copyright©2005 IFAC*

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1. INTRODUCTION

In solving many engineering problems, biological inspired algorithms have often shown to be highly efficient and effective. To name but a few, artificial neural networks allow systems to learn from experience (Sipper, 2002), genetic algorithm creates diversified answers for complex problems (Bentley, 1999), and swarm behavior inspired highly scalable multi-agent system (Wooldridge, 2002).

This paper focuses on the study of an engineering analogy of the human immune system known as artificial immune system (AIS) that protects our body from foreign antigens such as viruses and bacteria. Specific immune cells are responsible for identification and elimination of these attacking agents (Benjamini et al., 1996). In essence, the human immune system consists of two major parts, namely the innate immune system that comes naturally, and the acquired or adaptive immune system.

The multi-agent control framework that is developed in this paper is based on the acquired immune system. To highlight the design and the behavior of the control framework, two specific functionalities, namely the behavior detection and response activation mechanisms are discussed. In AIS, these relate to the immune recognition where abnormality situations are being identification and the general suppression mechanism where corresponding actions are performed by the network of cooperating agents.

To illustrate the behavior and to evaluate the effectiveness of the control framework, a number of experiments are conducted using a distributive material handling simulator developed with MATLAB. The results demonstrate the behavior of agent cooperation that is controlled using the AIS-based control framework.

The following section outlines the features of the immune system, which aims to bring out the key concepts of the system. Sections 3 to 5 introduce the basis of the two mechanisms presented, which is followed by Section 6 that describes the experimentation. Section 7 concludes the work and discusses our future plans.

2. BIOLOGICAL AND ARTIFICIAL IMMUNE SYSTEMS

In biological immune system, **innate immunity** consists of elements that are already present to defend against foreign bodies. These elements include skin, mucous membrane, and internal components such as fever, macrophages and chemical released by leukocytes to stop the effect of foreign bodies. **Acquired immunity** on the other hand supplements the innate system. Two major entities, namely, the T-lymphocytes (T-cells) and B-lymphocytes (B-cells) interact and perform the defensive activities against antigens. B-cells synthesize and secrete into the bloodstream antibodies with specificity against the antigen, the process is called humoral immunity. The T-cells do not make antibodies but identify invader to kill, they also help B-cells to make antibodies and activate macrophages to eat foreign matters (Playfair & Chain, 2001).

Amongst the diverse theories of immunology, there are essentially four unique functions that characterize the mechanism of immune system. These functions are:

Clonal Selection is the mechanism by which each B-cell makes antibodies that fit only one specific type of antigen, called its “cognate” antigen. When the specific B-cell binds to its cognate, the B-cell proliferates by cloning itself that recognize that same antigen. The newly cloned cells will become plasma B-cells and continue to produce and export huge quantities of antibodies continuously, which is equivalent to positive feedback. This is one of the key mechanisms in immunology.

Immunological Memory is a result of the small number of left over immune cells that remain alive after being activated and proliferated to destroy the foreign invaders. These leftover B and T cells become immunological memory of the system and are called Memory Cells. These cells are much easier to activate than novice immune cells.

The **Antibody Diversity** mechanism mix and matches segments of B-cell genes to create Modular diversity and Junctional diversity. Through this mix and match strategy, a small number of gene segments can create incredible antibody diversity.

The **Discrimination** action is a unique feature in the immune system for the discrimination of Non-Self Cells from Self Cells. Self Cells are the good cells that exist and work inside our body. Non-Self Cells are external elements that does harm to the system (antigen). The distinction and the recognition of foreign antigens are done by B-Cells and T-Cells, which allows the system to identify and annihilate harmful molecules and leave the good molecules (self-cells) behind.

As such, the immune system is a reactive system that is able to effectively identify abnormal entities and activities, learn from experience and solve problem with learnt knowledge, and generate new solutions for new situations. In essence, the system represents a network of automata that cooperate to achieve task autonomously.

Drawing analogy from an engineering perspective, the immune system is a highly distributed, dynamic, self-organizing, robust, multi-agent system having specific mechanisms for sensing, controlling and reacting to external and internal stimuli, which is more complete and superior than other biological system. The study of artificial immune system (AIS), which is the engineering counterpart, has recently gained much attention in various engineering disciplines (Ko et al., 2004; de Castro & Von Zuben, 2000; Hart et al., 2003; Ishiguro et al., 1997).

There are various studies AIS in the field of multi-agent control. The cooperative controls in (Lee et al., 1999) and (Lee & Sim, 1997) use group behavior mechanism of the immune system for autonomous mobile robots. A Distributed Autonomous Robotic System (DARS) that utilizes the AIS techniques shows a noticeable improvement in (Meshref & VanLandingham, 2000). An autonomous navigation is developed in (Michelan & Von Zuben, 2002) to investigate an autonomous control system of mobile robots based on the immune network theory. In addition, recent investigations undertaken by the authors (Lau & Wong, 2003) have shown that a more efficient distributive control framework can be achieved over a centralized control.

3. THE AIS-BASED CONTROL FRMAEWORK

In a generalized control hierarchy, a control system senses the salient information such as the state of the plant and demand, and detects any changes before corresponding control actions are issued with a view to satisfy the demand. Based on this hierarchy, the proposed AIS-based control framework mimics the behavior of the immune T-cells in recognizing antigens and performing defensive actions. We adapted such mechanism with two distinct functional blocks, namely, the Behavior Evaluator and the Action Modulator as shown in Fig. 1.

In terms of control system activities, the Behavior Evaluator is responsible for monitoring its environment for any changes, which is analogous to a

T-cell duty of identifying antigens; whereas the Action Modulator responses to the detected changes and generates corresponding actions, which is analogous to the killing of antigens by T-cells. The key functions of the two components are explained in the following sections.

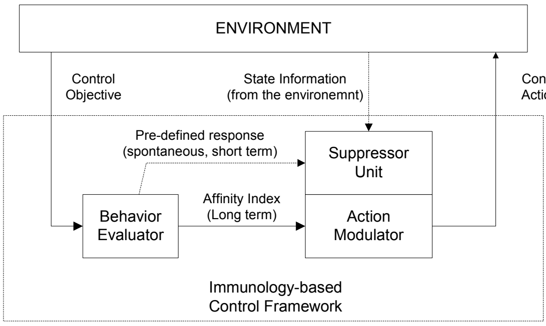

Fig. 1. The Artificial immune system-based control framework

4. BEHAVIOR EVALUATOR

The primary responsibility of the behavior evaluator is to evaluate information that is captured from the environment against the control objectives or demands, and generates an affinity index. A high index value corresponds to large adjustments is to be made, and vice versa. The behavior of this component is adapted from the immune recognition and discrimination functions. Through the evaluation of the binding affinity, self and non-self entities that correspond to desirable and abnormal behavior are differentiated.

The evaluation of the affinity index of the recognition process in a dynamic environment follows the definition of the binding affinity. In the context of material handling as focused in this paper, binding affinity, β_{ij} between an agent i and a task j is enumerated by the distance between an agent and a particular delivery task (d_{ij}), the task occurrence frequency (f_{ij}) and agent familiarity with such a task (r_{ij}) according to Equation 1 (Lau & Wong, 2004):

$$\beta_{ij} = w_1\left(d_{ij}\right)^{-1} + w_2\left(f_{ij}\right) + w_3\left(r_{ij}\right) \qquad (1)$$

where w_1, w_2 and w_3 are the scalar weightings of the three components. Specifically, $d_{ij(E)}$ is the Euclidean distance between an agent j and a task i on a two dimensional plane, where $d_{ij(E)}$ is given by:

$$d_{ij(E)} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \qquad (2)$$

f_{ij} is the frequency of occurrence of the particular task j and O_j is the number of occurrence of task j:

$$f_{ij} = \frac{O_j}{\sum_{x=1}^{m} O_x} \qquad (3)$$

Finally, r_{ij} compute the agent's familiarity with the particular task, which is evaluated using Equation (4).

$$r_{ij} = \frac{1}{R_{ijI}^{\,S_{ij}} \cdot R_{ijL}} \qquad (4)$$

The function r_{ij} is referred as the specificity matching function that determines the most suitable agent to a given task. Based on a symbolic coding scheme for representing the capability of an agent and the characteristics of a task, our framework adopts a string matching function to determine the best match of task to the set of available agent (Lau & Wong, 2004). Fig. 2 illustrates the capability coding scheme adopted.

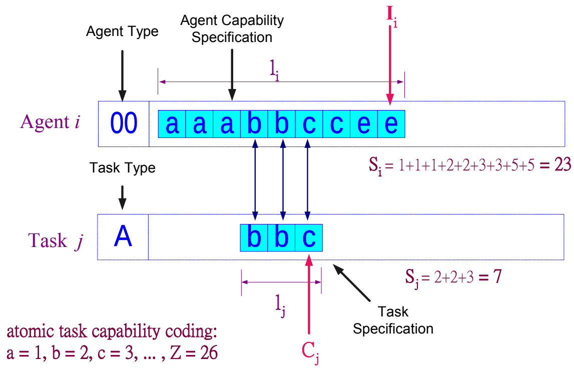

Fig. 2. The coding of an agent's capability and a task specification, and the corresponding parameters for computing the specificity matching function

Taking reference from Fig. 2, the corresponding indices for relative intelligence between an agent and a task, R_{ijI} ; the relative matching length of the capability and the task specification, R_{ijL} and the relative score, S_{ij} that highlights the efficiency between the capability and the task specification, are given by the followings:

$$R_{ijI} = \frac{\max\left[I_i\right]}{\max\left[C_j\right]}$$
$$R_{ijL} = \frac{l_i}{l_j} \quad \text{and} \quad S_{ij} = \frac{S_i}{S_j} \qquad (5)$$

5. ACTION MODULATOR

The Action Modulator evaluates the inputs from the behavior recognizer and the internal suppressor units that respond to different stimulations to produce the particular actions. The behavior exhibits is similar to the cell differentiation mechanism, in which cells develop aggressive or tolerant behavior in response to the type of cytokines present in the environment. When activated, these cells also release humoral signals to convert nearby cells to copy their behavior.

The suppressor units provide the explicit functionality of action selection, which is comparable to the function of cytokine signaling mechanism that performs intercellular communication and changes the condition of the environment. This is parallel to the elicitation or suppression of the aggressive behavior of the T-cells. Mapping this to our proposed control framework, an affinity threshold function for the jth antigen, K_j (Equation 6) is defined. The function provides a means to compute the threshold for the suppression or activation of an agent's activity towards a particular task or goal. The function obtains dynamic information including the agent's location and capability, and is controlled by (a) the binding affinities β_{ij} of all the required and qualified agents for a particular task j, (b) the total number of qualified agents that has detected a task j, η_{ij} and (c) the total number of agents that is required to tackle task j, η_{re}.

$$K_j = \frac{\sum_i \beta_{ij}}{\eta_{ij} \cdot \eta_{re}} \qquad (6)$$

Based on the value of K_j evaluated, the suppressor units in the Action Modulator then control the suppression or activation of actions corresponding to a particular task in accordance to the prevailing affinity index. Typically, when the affinity index exceeds K_j, the activity is suppressed and vice versa.

6. IMPLEMENTATION AND EXPERIMENTAL STUDIES

To evaluate the operation and performance of the AIS-based control framework in the context of automated material handling using a number of AGVs representing the AIS-agents, an AIS simulator is developed. A number of experimental cases were set up based on a fleet of AGV that operates in a 2-D warehouse with a number of tasks, which may be cargos that required build-up or unpacking, or required delivery to certain location, that distribute across the area of the warehouse. Fig. 3 illustrates a typical map of a work cell in a warehouse.

A number of experiments are carried out with different initial locations of the fleet of AGVs under the proposed distributed control framework as well as using a conventional centralized control. To highlight the cooperative feature of cooperating agents or AGVs, a constraint is imposed such that a group of four AGVs is required to handle a particular task. Fig. 4 and Fig. 5 show typical trajectories taken by the fleet of AGVs when handling a task.

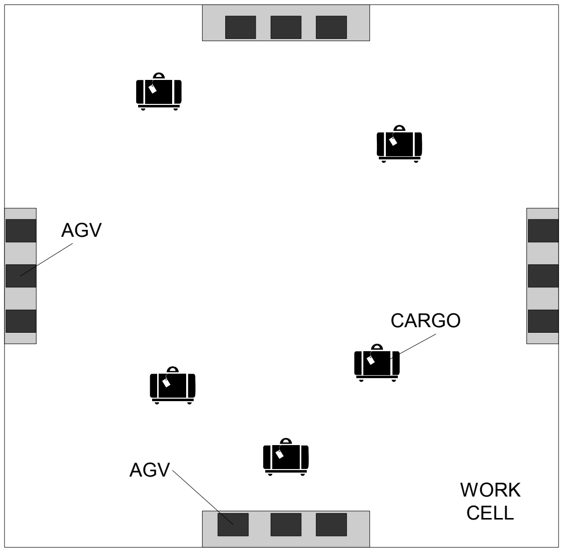

Fig. 3. A typical work cell of an automated material handling system with AGVs initially parked at the side depots and cargo distributed within the work cell.

For the centralized control, an agent initially explores the environment and searches for tasks independently until a task is being recognized. Such an agent then resumes the role of a team leader and starts to recruit helpers to complete the task (Fukuda et. al, 1991). Fig. 6 compares the efficiency of task achievement between the centralized and AIS-based control paradigms. Two sets of results are obtained for the centralized control (doted lines) and AIS-based control (solid lines), with different AGV task sensing and communication ranges.

It is shown that for the centralized control, a gradual decrease in the number of steps taken by the AGVs for task completion when the number of AGVs deployed increase is observed. This is mainly attributed to the increase in workforce within a workplace. For the AIS-based control, a significance improvement in task completion is observed when the number of AGVs has reached a certain level and then saturates when the number of AGVs deployed exceeds twenty. The results indicate that (a) the AIS-based control framework is not as sensitive as the centralized control in the initial parameter settings such as location of AGVs and sensory ranges, and (b) the improved in efficiency of task completion by the AIS-based control.

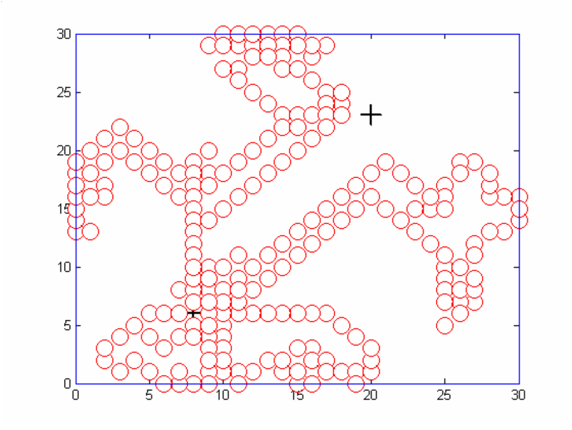

Fig. 4. Typical trajectories of the AGVs under centralized control

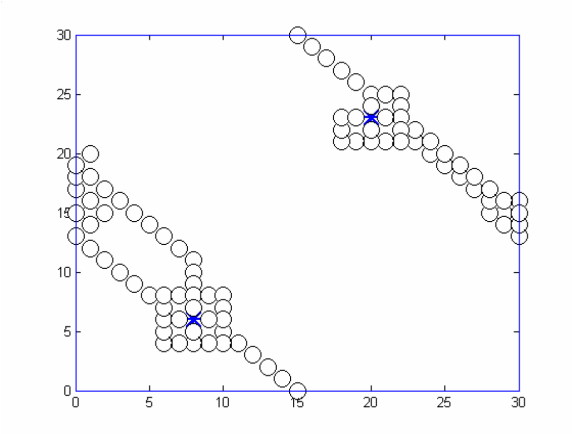

Fig. 5 Typical trajectories of the AGVs under the AIS-based control framework

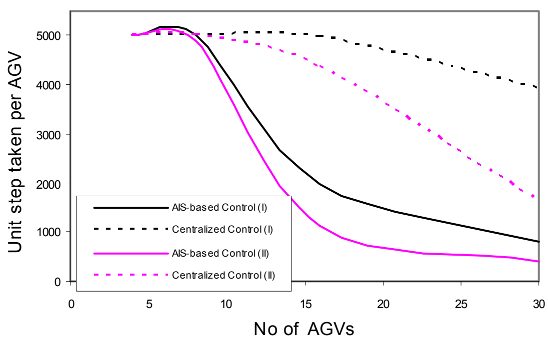

Fig 6. Efficiency of the proposed AIS-based control vs. a typical centralized control

To further explore the action of the AIS-based control framework, the action of the Action Modulator is studied. The suppressor units in the Action Modulator generate suppression/activation signals to enhance the operation of the control framework for task achievement. Further simulation studies are performed to observe the action of these suppression/activation signals.

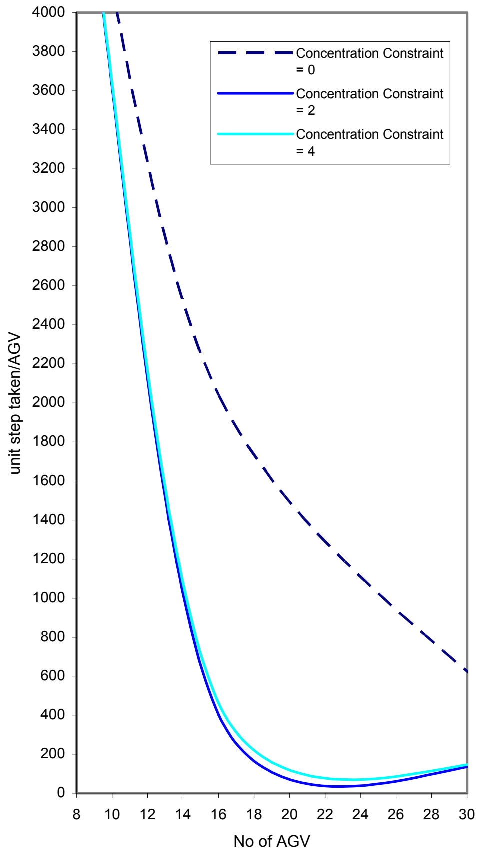

Fig. 7. The performance of the AIS-based control framework in performing material handling task with different levels of suppression

In the simulation study of the AIS-based control framework, the action of the Action Modulator where suppression signals are generated by the suppressor units is particularly studied by observing the effects of the suppression signal on the AGVs while performing a task. Different suppression levels are applied to the AGVs when they are performing material handling tasks. Fig. 7 shows the differences in performance when the Action Modulator is activated with no suppression signal generated (dotted line), and when suppression signals are generated and applied to the AGVs (solid line). In this study, the implicit function of the Action Modulator is to regulate the concentration of the AGVs within a region. In essence, the suppressor units compute the aggregation or density of AGVs with the vicinity based on the computation of the prevailing binding affinity and the affinity threshold for individual AGV according to Equations 1 and 6. It is observed that a more efficient system is resulted when the Action Modulator is in action with a maximum of 75% increase in efficiency is obtained when 23 AGVs are in operation in the case of the simulation study. In fact, the same observation is obtained in biological immunity where the concentration of the immune cells is regulated by the biological immunity system to significantly enhance the performance in fighting foreign invaders.

7. CONCLUSION

This paper presents a multi-agent control framework that is inspired from the biological immune system, generally known as an artificial immune system. The paper describes the two major functional blocks, namely, the Behavior Evaluator for task detection and the Action Modulator for regulating the inter-activity of individual agent. Based on the mathematical modeling of the AIS-based control framework, an implementation of the framework is produced for the case of automated material handling. Through simulation studies, the AIS-based control achieves high level of flexibility and performance in coordinating other of AGVs in the vicinity in a dynamic environment. The studies show that the AGVs under the control of the AIS-based control framework response to the dynamically changing environment and showing concerted emergent behavior as a result of local interactions among AGVs. The results of the study established that the fully autonomous and distributive nature of the AIS-based controlled framework outperformed a typical centralized control paradigm in additional to other desirable features including self-organizing, adaptive and fault tolerant. Currently, while we are working on the formalization of the other components of the AIS-based control framework, experimentations with using laboratory mobile vehicles for cooperative task handling is underway.

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