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A cooperative control model for multiagent-based material handling systems

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Abstract

This paper presents an Artificial Immune System (AIS)-based model for cooperative control of multiagent systems. This cooperative control model describes collective behaviors of autonomous agents, known as the AIS agents that are exemplified by the regulated activities performed by individual agents under the computation paradigm of Artificial Immune System. The regulations and emergence of agent behaviors are derived from the immune threshold measures that determine those activities performed by the AIS agents at an individual level. These threshold measures together with the collective behavioral model defined the cooperative control of the AIS-based control framework under which AIS agents behave and act strategically according to the changing environment. The cooperative control model is presented under the three domains, namely exploration, achievement and cooperation domains where AIS agents operate. In this research, we implemented the proposed cooperative control model with a case study of automated material handling with a group of AIS agents that cooperate to achieve the defined tasks.

Keywords: Artificial Immune System; Multiagent system; Distributed control

1. Introduction

The incorporation of various biological metaphors to the derivation of engineering theories and solving engineering problems has enriched the developments of engineering science. A large number of undertakings have attempted to mimic the mechanisms inherent in the natural world to solve complex problems. These human-made analogies of the natural systems can be exemplified by artificial neural networks, evolutionary algorithms, genetic algorithms, swarm intelligence, etc. They provide new insights, inspiration, concepts and solutions towards solving engineering problems, such as automatic control, machine learning and scheduling problems, some with proven track records.

A new emerging biological metaphor that adopts the characteristics of the immune system is called Artificial Immune System (AIS). The immune system is a highly distributed multiagent system having complex and sophisticated mechanisms for the regulation of its components such as antibodies, tissues and molecules. The properties of distributive control and self-organization impart a high degree of robustness to create various intelligent systems, algorithms and methodologies for solving a wide spectrum of problems ranging from autonomous robotics (Ishiguro, Ichilkawa, Shibata, & Uchikawa, 1998; Singh & Thayer, 2001; Watanabe, Ishiguro, & Uchikawa, 1999), computer security (Harmer, Williams, Gunsch, & Lamont, 2002; Kim & Bentley, 1999; Nino & Beltran, 2002), to medical diagnostic systems (Polat & Güneş, 2007; Polat, Sahan, & Güneş, 2006).

In our previous works (Lau & Wong, 2003), we proposed a behavioral model to define the activation and manipulation of agent behavior, with a view to develop a

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control framework that has the capacity to manage, coordinate and schedule multiagents by imitating the human immunity mechanism. The model determines how agents of different intelligence levels achieve tasks in a dynamic environment through information exchange between agents. The study have shown that an with the behavioral model in place, an AIS-based control framework can be developed that is efficient in coordinating a group of autonomous agents with diverse capabilities in a distributed environment, and the result shed lights into the development of a truly decentralized and self-organized multiagent system.

Being motivated by earlier results (Lau & Wong, 2003) and inspired by the properties of self-regulation in biological immune systems, this paper develops a cooperative control model that is based on the behavioral model to provide an effective methodology to coordinate and control multiagent systems. The core of the control model exploits the immunity-based regulation mechanisms to emerge group collective behaviors and cooperative strategies in achieving global goals. Through the exposition of the immune system characteristics, agents in the framework are abstracted as independent entities, known as AIS agents, which are operating in a multiagent system that carry local information, search for solutions and exhibit robust behavior to accomplish tasks.

Within the scope of the proposed control model, the adopted immunity-based regulation mechanism comprised three important threshold measures that regulate the activities of AIS agents and provide effective coordination for multiagent systems under three domains, namely, exploration, achievement and cooperation domains. These three domains represent a typical operation cycle of AIS agents in performing activities such as exploration, collaboration, tackling tasks, etc. In each of these domains, a threshold measure is introduced such that AIS agents act and behave accordingly under different situations encountered. These threshold measures being the key elements for effective agent coordination form the heart of the immunity-based regulation mechanism.

Specifically, the three threshold measures that govern the regulation mechanisms are: (i) wandering threshold; (ii) affinity threshold and (iii) activation threshold. The wandering threshold is employed under the exploration domain. In particular, the number of AIS agents that perform exploration activities are regulated within a wandering zone. The agents are regulated to perform either random exploration or dispersion under the control of the wandering threshold. The affinity threshold is employed under the achievement domain. Upon detecting a task during exploration, an AIS agent will evaluate its feasibility to tackle the task using the affinity threshold. The agent will either be activated or suppressed to approach its targeted task based on the affinity between the agent and the task. The activation threshold is employed under the cooperation domain. This threshold regulates the number of agent to participate in a cooperative task. Through receiving stimulation signals, a responding agent will either be activated or suppressed to join a cooperative task by the activation threshold.

This paper proceeds as follows: Section 2 provides an overview of the human immune system and in particular, the regulation mechanism. Section 3 introduces the AIS-based cooperative control model under the three domains. The domain of our study, namely, material handling systems is presented in Section 4, which is followed by the simulation study of Section 5. Section 6 discusses the results and Section 7 draws the conclusion.

2. Background

2.1. Biological immune system

In general, biological immunity is classified into innate immunity and acquired immunity. Innate immunity mediates the initial protection against infections. Acquired immunity, which develops more slowly, mediates the subsequence defense against infections.

Innate immunity is inborn and unchanging. It provides resistance to a variety of antigens during their first exposure to a human body. Innate immunity therefore operates non-specifically during the early phase of an immune response. This general defense mechanism is known as primary immune response which is slower and less protective. In addition to providing the early defense against infectious, innate immunity enhances acquired immunity against the infectious agents.

Acquired immunity develops during the lifetime of a person and is based partly on the person's experiences. It is the form of immunity that has an exquisite specificity for foreign antigens and is activated during the first exposure to antigens. This antigen-specific acquired immunity is activated to eliminate antigens by its elements such as antibodies and immune cells (Sheehan, 1997). When an antigen binds to the surface receptors of an immune cell, this interaction sensitizes the proliferation and differentiation of the population of immune cells specific to that individual antigen. After the elimination of the antigen, some of the immune cells become memory cells for action on the reoccurrence of the same antigen in the future. Due to this immunologic memory, acquired immunity is able to mount a more rapid and effective immune response in the subsequent exposure to the same antigen. This is known as secondary immune response.

In essence, the immune system is controlled by the action of a large number of regulatory and effector molecules. They have various cell surface receptors and soluble molecules such as interleukins that can transmit signals between immune cells to eliminate foreign antigens. The most important cell type is the white blood cells that are known as lymphocytes (Cruse & Lewis, 1999).

Lymphocytes are the only cells with specific receptors for antigens and are therefore the key mediator of acquired immunity. There are two major classes of lymphocytes: B cells and T cells. They are created from stem cells in the bone marrow. B cells mature in the bone marrow and T cells in an organ called thymus. Mature cells are transported throughout a body via blood stream and the peripheral lymphoid organs, where they reside and express specific receptors when antigens are presented. Naïve lymphocytes are mature B or T cells that has not encountered antigen previously, or is the progeny of an antigen-stimulated mature lymphocyte during cell differentiation. Fig. 1 depicts the maturation process of B and T cells.

In particular, B cells are the cells of humoral immunity. They carry the genetic instructions to produce antibodies, one of the major protective molecules in the body, of unique antigen specificity. Antibodies serve as the B cell receptors that recognize antigens and initiate the process of cell activation. The class of antibody and the kinetics of its production depend largely on the number of time the host has seen the antigens. In a secondary response, which is a more rapid and stronger response, the antibodies show much higher affinity to the eliciting antigens. This change in antibody class and affinity is due to B cell activation, differentiation and maturation. The interactions between immune cells that exhibits the immune regulation activity is further explained in the following section.

2.2. Regulation in the immune system

Normally, the immune system is in a resting or equilibrium state for a healthy individual. This equilibrium state is perturbed when antigens are introduced into the individual. An immune response will then be triggered to eliminate the antigens. When response to the antigens is no longer required, the immune response will restore the immune system to an equilibrium state. This activation and restoration of the immune system that is governed by the immune response, is subject to a variety of regulation or control mechanisms.

As discussed previously, an immune response is triggered by the activation of lymphocytes during the process of self-non-self discrimination. Activated lymphocytes

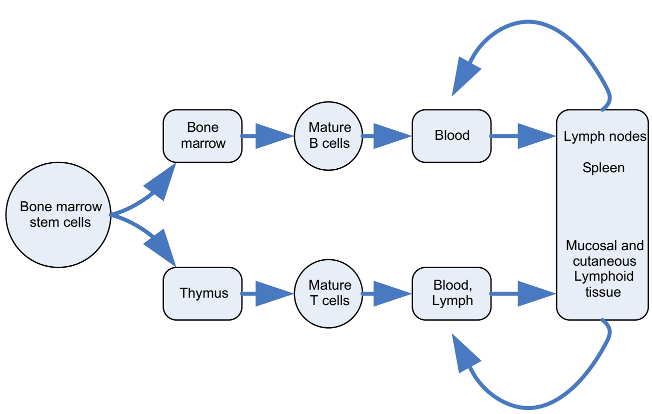

Fig. 1. Maturation of B and T cells.

secrete antibodies to kill antigens. An insufficient number of antibodies can cause immunodeficiency and increases susceptibility to infection. Contrarily, an excessive number of antibodies can cause autoimmune diseases. Hence, the concentration of antibodies produced should be regulated properly in order to mount an effective immune response.

Antibody exhibits negative feedback control over its own production (Nino & Beltran, 2002; Roitt, Brostoff, & Male, 1998). This feedback control allows the antibody to suppress itself for further synthesis. In particular, B cells, which are lymphocytes that are produced and mature in bone marrow, are activated by antigens to produce antibodies. When the concentration of the antibodies is too high, the antibodies will bind to B cells in order to inactivate the production of the antibodies.

The strength of the binding between an antibody and an antigen is known as affinity (Breitling & Dübel, 1999). Apparently, antibodies that have a high affinity with an antigen will have a higher probability in successful binding. As a result, B cells that have a weak affinity with an antigen require the activation by T cells, which are lymphocytes that mature in the thymus, for successful binding. This kind of T cells is called helper T cells. On the other hand, a subpopulation of T cells, that is called suppressor T cell, is able to diminish or suppress the immune reactivity of B cells (Eales, 1997). The suppression of immune response is carried out by inhabiting antibody formation or down-regulating the ability of lymphocytes to mount an immune response.

In summary, the immune regulation mechanism constitutes the core of the immune system. Based on this regulation mechanism, lymphocytes can be self-activated and self-suppressed to provide immune responses. The overall immune response is a consequence of the balance between helper T cells and suppressor T cells. Such a balancing effect has demonstrated the self-organization and self-regulation properties of the immune system.

3. AIS-based control framework

In the AIS-based multiagent control framework, agents are abstracted as independent entities, known as AIS agents. These agents are operating as a multiagent system and they carry local information, explore their local environment, search for solutions and exhibit distinct behavior to accomplish tasks.

This conceptual framework consists of four elements as depicted in Fig. 2. These elements establish a comprehensive framework for the control at both individual and collective levels. The architecture of an AIS agent and the responses manipulation mechanism of individual agent constitute the individual level, whereas the behavioral model and the regulation mechanism constitute the collective level of the control framework. These elements are inter-related with each other. They establish a fully distributed system with agents having autonomy in decision-making, communication, action generation and collaboration.

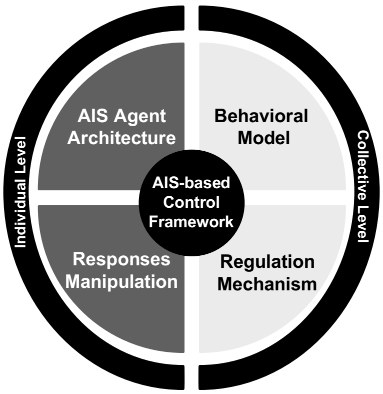

Fig. 2. An overview of the AIS-based control framework.

3.1. Individual level

The individual level defines the architectures for each individual agent in a multiagent system. This level considers the definition, the flow of control, and the intelligence of an agent together with how the intelligence is captured. In the control framework, all AIS agents have the same architecture for their internal control. The disparities between agents are distinguished from their degree of intelligence. Hence, AIS agents have different level of capabilities but an identical internal structure.

The AIS agent architecture is composed of a series of functions. It defines the operational mechanism of an AIS agent. The operational mechanism provides a set of immunity-based threshold measures that guides and determines the behavior of individual AIS agents in response to the changing environment. Through employing these threshold measures, AIS agents are able to demonstrate effective coordination in which new events and changes in the workplace can be investigated efficiently.

On top of the architecture for internal control, an AIS agent has a pre-defined set of capabilities that determine their fundamental intelligence and performance capacity. The differences in agents' intelligence level give rises to heterogeneity for the overall system. The fundamental intelligence can be enhanced through inter-agent communication or via explorations in the environment. A novel responses manipulation algorithm is developed based on the theory of innate and acquired immunities, to describe how AIS agents generate appropriate responses and new capability sets in problem solving (Lau & Wong, 2003).

3.2. Collective level

In addition to the internal control of an AIS agent regarding individual level, control that coordinates agents with the environment is equally vital to a multiagent system. This responsibility is delegated to the control at the collective level. The collective level defines the interaction, coordination, and organization between agents and their environment. In the proposed control framework, the collective level is mainly established by self-regulation and self-organization strategies, which depend largely on the immunity-based threshold measures presented in this paper. Since the threshold measures are defined and implemented in the AIS agent architecture, the individual level acts as a platform that supports the activities at the collective levels.

The immune system is a special type of multiagent system where each agent of immune elements has specific behavior patterns and functions for a particular antigen. This characteristic is adopted by AIS agents to generate collective behaviors based on the environment as well as individual behaviors. Through the exhibition of immune inspired behaviors, self-regulation and self-organization activities are performed. The immunity-based regulation mechanism is therefore introduced by the fusion of the immune inspired behaviors and threshold mechanisms, which are the corresponding components of the collective and individual levels. Such a regulation mechanism regulates AIS agents under which they exhibit cooperative activities for effective coordination.

3.3. AIS-based responses

In the control framework, the actions performed by AIS agents are determined by the responses manipulation algorithm (Lau & Wong, 2003) developed based on the biological immune responses where generation of an immune response involves a specific sequence of actions including antigen recognition, activation of lymphocytes, elimination of antigens, and memory (Abbas & Lichtman, 2001). By drawing analogy from biological immunity, four key responses are introduced and adopted by the AIS agents described in this paper.

3.3.1. Non-specific response

Non-specific response is equivalent to innate immunity of the immune system. Innate immunity is the first general defense that provides resistance to a variety of antigens, non-specific response deals with tasks that are general and simple to a particular operation. Non-specific response is represented by atomic abilities such as grouping and counting of goods in the context of material handling.

3.3.2. Specific response

AIS agents tackle tasks through matching of their capabilities with task complexities. Specific response is executed when agents encounter more complex tasks. These specific tasks need more advanced capabilities that are outside the scope of non-specific response. AIS agents are required to generate a new set of capabilities from the atomic abilities through capability manipulation. This is analogous to biological immunity where antibodies are able to form new binding patterns for specific types of antigens (Breitling & Dübel, 1999).

3.3.3. Acquired response

AIS agents generate new capabilities and store them in their memory as acquired response for future reference.

On re-encountering the same complicated task, agents no longer require to manipulate its capabilities to perform specific response. A much faster acquired response is available after the first encounter with such tasks. The process of executing specific response and giving rise to acquire response is similar to the antigen-specific defense mechanism of acquired immunity. An acquired immune response is a secondary response that occurs upon second and subsequent exposure to an antigen. The secondary response is characterized by more rapid kinetics and greater magnitude relative to the primary response that occurs upon the first exposure (Abbas & Lichtman, 2001).

3.3.4. Passive response

Passive response is similar to the idea of vaccination of biological immunity which is a process of intentionally eliciting acquired active immunity in an individual by administration of a vaccine. A vaccine is capable of stimulating a sufficient number of lymphocytes to trigger an immune response against virus infection (Cruse & Lewis, 1999; Elgert, 1996). Passive response is primarily introduced for agent cooperation and to control the performance of collective activities. Central to a passive response, stimulation signals are employed to recruit agents for cooperative tasks. An AIS agent that detects a cooperative task (initiating agent) and needs to recruit more agents for the task will send stimulation signals to activate their surrounding agents. Agents who have received such stimulation signals will be activated and approach the cooperative task. These responding agents tackle the cooperative task by passive response as they are activated instead of first detected the task themselves.

In this paper, the cooperative control model that provides an effective methodology to coordinate and control multiagent systems is presented. The model describes collective behaviors of agents based on those regulated activities performed by individual agents under the computation paradigm of Artificial Immune System. The control model is presented under the three domains namely, exploration, achievement and cooperation. These three domains represent the entire operation cycle of AIS agents to perform activities ranging from exploration to collaboration. In each of these domains, a threshold measure is presented such that AIS agents exhibit specific actions and behaviors under different situations encountered. These threshold measures, which are the key elements for effective agent coordination, form the heart of the immunity-based regulation mechanism.

4. Cooperative control model

4.1. Exploration domain

The ultimate goal of AIS agents in the exploration domain is to detect tasks. The main immunity-based regulation mechanism adapted in this domain is to perform concentration control of immune cells. The immune system is said to be in a resting or an equilibrium state when no foreign antigens are presented. The concentration of immune cells is balanced throughout the immune system when it is in an equilibrium state. In view of this, the distribution of AIS agents in the exploration stage is controlled to enhance the overall searching efficiency in the multiagent system. This mechanism for regulating the concentration is controlled by the wandering threshold that controls the dispersion activity of AIS agents when a large number of them are crowded within the same proximity during exploration.

AIS agents explore the environment, search for tasks and identify tasks in the exploration domain. The elements of the AIS-based control framework that are responsible for these exploration activities are listed in Table 1.

4.1.1. The exploration algorithm

As the main goal of AIS agents in the exploration domain is task detection, the algorithm starts by assuming a task detection index for each AIS agent working in a workplace U. Let ε_j be the task detection index, which is a Boolean value that indicates if any task is located within the sensory range, φ_j, of Agent j, A_j

$$\varepsilon_j = \begin{cases} TRUE & \text{if } |L(A_j) - L(T_a)| \leqslant \varphi_j \\ FALSE & \text{if } |L(A_j) - L(T_a)| > \varphi_j \end{cases}, \quad T_a \in T \tag{1}$$

where the location indexes of an AIS agent, A_j, and a task, T_a, in a two dimensional plane is denoted by $L(A_j)$ and $L(T_a)$ respectively.

If nothing has been detected by A_j, that is $\varepsilon_j = FALSE$, A_j continues to explore the environment through pseudo-random motion. In this case, the next location of an AIS agent is generated by a function called pseudo-random generator – $RAN(\ )$. This function returns the next location of A_j from a set of possible next locations based on a discrete uniform distribution. The next location of A_j is denoted as nL_j. The set of possible next locations of A_j is denoted as P_j. P_j is a set of coordinates that is defined by the perimeter of an agent's current position, $L(A_j) = (x_j, y_j)$. The size of the perimeter is given by radius r that is measured from $L(A_j)$

$$\mathrm{RAN}(nL_j) \in P_j \tag{2}$$

$$P_j = \{((x - x_j)^2 + (y - y_j)^2) = r^2\} \tag{3}$$

Eqs. (2) and (3) define how A_j generates its next position during exploration under normal circumstances. That is, no concentration constraint is applied to control the exploration activities of AIS agents.

Table 1
Functions that define the exploration algorithm

AIS agent architecture (Individual level)
Wandering threshold
Binding affinity
Specificity matching
AIS-based behavioral model (Collective level)
Explore behavior
Disperse behavior

In the proposed control framework, exploring agents have two different behaviors: the *Explore* and *Disperse* behaviors, which are represented as $A(E)$ and $A(D)$, respectively. Concentration constraint is applied to these agents, when the total number of $A(E)$ in a wandering zone has exceeded the system's wandering threshold, Ψ. In this case, the set P_j is no longer defined by Eq. (3) as dispersion among AIS agents will take place. A_j is therefore required to generate a new set of P_j for the dispersion activities.

During dispersion, a separation-distance, z_j, should be maintained between the exploring agents in a wandering zone. The set of exploring agents, $A(E)'_j$, within the sensory range, φ_j, of A_j is defined as

$$A(E)'_j = \{A_a\} \quad \text{where } |L(A_a) - L(A_j)| < \varphi_j, \quad A_a \in A \tag{4}$$

A_j compares each element in the set P_j with each element in the set $A(E)'_j$. The distance between a possible next location of A_j, $L(p_0)$, and the location of an exploring agent, $L(A_a)$, within the wandering zone is denoted by v_0, where

$$v_0 = |L(p_0) - L(A_a)| \quad A_a \in A(E)'_j, \ \forall v_0 \in P_j \tag{5}$$

If $z_j > v_0$, the possible next location p_0 will be deleted from the set P_j. If $z_j < v_0$, the possible next location v_0 will be kept in the set P_j as one of the next possible location for A_j. Hence, when the total number of exploring agent, $\sum A(E)$, in a wandering zone is greater than ψ, A_j with the *Disperse* behavior will generate a set P_j as follows:

$$P_j = \{p_a, p_b, p_c, \ldots, p_n\} \quad \forall z_j > v_n, \ \sum A(E) > \psi \tag{6}$$

Similar to random exploration, AIS agents who are performing dispersion activities will generate the next position, nL_j, according to Eq. (2) by taking reference from the set P_j that is computed by Eqs. (5) and (6).

If at least one task has been detected by A_j, that is $\varepsilon_j = TRUE$, A_j employs the binding affinity function to select a particular task, T_i, for tackling. T_i is defined as the targeted task that is identified by A_j during exploration. Let τ_j be the set of tasks identified by A_j, such that

$$\tau_j = \{T_a\} \quad \text{where } |L(A_j) - L(T_a)| < \varphi_j, \quad T_a \in T \tag{7}$$

The binding affinity, β_{aj}, between A_j and T_a is enumerated by Eq. (8) with the parameters: (i) the Manhattan distance between A_j and $T_a - d_{aj}$; (ii) the associated task occurrence index – f_{aj}; and (iii) the specificity matching function – r_{aj}. A set of binding affinity, β'_j, are evaluated for A_j, which is given by Eq. (9)

$$\beta_{aj} = w_1(d_{aj(M)})^{-1} + w_2(f_{aj}) + w_3(r_{aj}) \tag{8}$$

$$\beta'_j = \{\beta_{aj}\} \quad \forall T_a \in \tau_j \tag{9}$$

In general, a task with the highest binding affinity value will be chosen as T_i, which is the targeted task for A_j. Hence, the ultimate goal of A_j in the exploration domain, which is to search for the most suitable task to tackle, is defined as

$$T_i = T_a(\max[\beta_{aj}]) \quad \text{where} \max[\beta_{aj}] \in \beta'_j \tag{10}$$

After fulfilling the ultimate goal of the exploration domain, A_j will enter the achievement domain. In other words, A_j is initiated for task tackling, and the targeted task has led to the emergence of Agitate behavior.

4.2. Achievement domain

The ultimate goal of AIS agents in the achievement domain is task completion. The mechanism enhances the efficiency in task completion in two main aspects. First, at the individual level, AIS agents perform different activities to complete a task. For example, AIS agents execute a specific response to deliver a task from one workstation to another. Second, at the collective level, AIS agents are evenly distributed over a workplace so as to enhance the overall task completion efficiency. For example, if there are already sufficient numbers of agents approaching Task i, Agent j with a lower affinity that has just targeted Task i during exploration will not approach Task i further. This second aspect at the collective level takes the dynamic situations, such as the locations, behaviors and interaction of AIS agents, into account. Among these situations, the interaction between AIS agents is one of the most important issues that affect the efficiency of task completion in the achievement domain.

The activities involve in task completion are solely governed by the responses manipulation function. It is an action generator that allows AIS agents to execute various responses for task tackling. Although AIS agents can effectively provide different actions according to the requirements and complexities of tasks, they could not interact effectively in a dynamic situation through responses manipulation alone. As a result, the affinity threshold is employed as the second immunity-based concentration constraint for achieving a balanced distribution of AIS agents in the achievement domain.

In biological immunity, an immune cell will stimulate other cells in response to a particular kind of antigen. When the concentration of the responded cells is too high, special signals will then be sent to suppress the activated cells in order to balance and regulate the antibody concentration (Eales, 1997). According to this concept, the affinity threshold is introduced to control the activation and suppression of an AIS agent's activity in response to a targeted task. The threshold regulates the number of AIS agents to accomplish tasks, and facilities the distribution of AIS agents in a workplace. AIS agents perform response manipulation and evaluate affinity thresholds in parallel. Hence, AIS agents can simultaneously accomplish tasks and accommodate dynamic situations efficiently. The components of the AIS-based control framework that are related to the achievement algorithm are listed in Table 2.

4.2.1. The achievement algorithm

AIS agents approach a targeted task and complete the task in the achievement domain that consists of two main processes working in parallel. First, AIS agents approach

Table 2
Functions that define the achievement algorithm

AIS agent architecture (Individual level)	
Affinity threshold	
Responses manipulation	
Capability manipulation	
AIS-based behavioral model (Collective level)	
Agitate behavior	
Achieve behavior	

a targeted task based on the affinity threshold. Second, AIS agents complete the task by the responses manipulation function.

In this case, Task i or T_i, is the targeted task that has been identified by Agent j, i.e., A_j, in the exploration domain. A_j with the Agitate behavior then moves forward to T_i. In the meantime, A_j evaluates its feasibility of tackling T_i using the affinity threshold, K_i (Eq. (11))

$$K_i = \frac{\sum_j \beta_{ij}}{\eta_{ij} \cdot \eta_T} \quad \forall A_j \in A'_i \tag{11}$$

Corresponding to the three factors presented above, the three parameters of K_i are: (i) the number of agents required to tackle Task $i - \eta_T$; (ii) the total number of agents that have targeted at Task i at a particular instance – η_{ij}; and (iii) the binding affinities associated with Task i – β_{ij}.

K_i are evaluated according to the movement and interaction of the set of agents, A'_i, that have targeted at the same task, T_i. K_i is computed recursively until an AIS agent in the set A'_i has been activated successfully, and has reached the task tackling area of T_i. Hence, a task that has been identified and targeted by A_j during exploration will have a status of true if its binding affinity value exceeds the affinity threshold

$$T_i = \begin{cases} TRUE & \text{if } \beta_{ij} > K_i \\ FALSE & \text{if } \beta_{ij} < K_i \end{cases}, \quad A_j \in A'_i \tag{12}$$

If A_j is not capable of tackling T_i, that is $T_i = FALSE$, the activity is suppressed. A_j will remove T_i from its short-term memory and search for other tasks with the *Explore* behavior.

If A_j is capable of tackling T_i, that is $T_i = TRUE$, the activity is activated. A_j will be agitated and will move toward to T_i with the Agitate behavior. The next location, nL_j of A_j in this case is determined by Eqs. (13) and (14)

$$D = |L(T_i) - L(p)|, \quad p \in P_j \tag{13}$$

$$nL_j = \min[D] \tag{14}$$

A_j with the Agitate behavior will approach its targeted task, T_i, by selecting the next location, p, from the set P_j that has a minimum distance away from T_i.

When A_j has entered the task tackling area of T_i, A_j will manipulate an appropriate response to accomplish T_i. The responses manipulation algorithm of A_j in task tackling is as follows:

```
IF (cooperativeTask)
  Passive Response
ELSE
  Match [Aj (capability chain), Ti (task complexity chain)]
    IF (Match = TRUE)
      Non-specific Response
    ELSE
      Match [Aj (acquired capability), Ti (complexity)]
        IF (Match = TRUE)
          Acquired Response
        ELSE
          newCapability = Manipulate (atomic abilities)
          Specific Response
```

In this algorithm, *Match* is the absolute string matching function. This function compares the capability chain of an AIS agent with the complexity chain of a task. Since the capability chain is represented by a chain of atomic abilities, *Match* returns *TRUE* if the pattern of the task complexity chain matches exactly with a segment of atomic abilities in the agent's capability chain. *Manipulate* is the capability manipulation function. This function rearranges the sequence of atomic abilities in a capability chain with a view to generate a new set of capabilities that is required for tackling a new and complex task.

After achieving T_i, an operation cycle of an agent is said to have completed. A_j will go back to the exploration domain with the *Explore* behavior, and start a new operation cycle by searching a new task.

4.3. Cooperation domain

The ultimate goal in the cooperation domain is the achievement of cooperative tasks. The cooperation domain only describes explicit cooperation actions among AIS agents. AIS agents are categorized into two main types in this domain: initiating agents and responding agents. An initiating agent is an AIS agent that transmits stimulation signals to other agents within its communication range, after it has reached the task tackling area of a cooperative task. A responding agent is an AIS agent that receives a stimulation signal and attempts to participate in cooperative tasks.

The immune activation threshold is employed and adapted in the cooperation domain. In biological immunity, cell-to-cell signaling is one of the major mechanisms for immune cell activation. The immune activation threshold is a minimum T cell signal required to elicit an immune response. The generation of this signal depends on two main factors: (i) the concentration of foreign antigens present in the system, and (ii) the stimulation intensity evoked by the antigens. These two factors control the concentration of immune cells that should be activated for a particular class of foreign antigens. Thus, the immune activation threshold regulates the activation of an immune cell in response to a given antigen.

Based upon the immune activation mechanism of biological immunity, an immunity-based activation threshold (Eq. (15)) is derived for the proposed control framework. The threshold aims at effectively coordinate AIS agents for cooperative activities. It is the third threshold measure of the proposed control framework that regulates an appropriate number of AIS agents to participate in cooperative tasks. The components of the AIS-based control framework that are responsible for the cooperation algorithm are listed in Table 3.

$$\Gamma_i = W_{ij(\min)} + (1 - \zeta_i) \cdot \mu_i \tag{15}$$

Γ_i, consists of three parameters: (i) the minimum activation index among the set of responding agents – $W_{ij\,(\min)}$; (ii) the average stimulation level evoked by a cooperative task – μ_i; and (iii) the relative responding level – ζ_i.

4.3.1. The cooperation algorithm

Cooperation between AIS agents is mainly instigated by stimulation signals. A stimulation mechanism is introduced to effectively coordinate AIS agents in performing cooperative activities. The stimulation mechanism consists of three primary elements that are regarding a cooperative activity: (i) stimulation signals send by an initiating agent, (ii) an activation index of a responding agent; and (iii) an activation threshold that supervises the activation and suppression of a responding agent.

The cooperation algorithm starts by assuming a cooperative task, T_i, that has been identified and targeted by an agent, A_j, during exploration. When A_j with the *Agitate* behavior has successfully reached the task tackling area of T_i, A_j will become an initiating agent for T_i. A_j transmits stimulation signals to the set of agents, A'_j, within its communication range, α_j. Agents in the set A'_j must be with the Explore or Disperse behaviors in order to be qualified as responding agents

$$A'_j = \{A_R\} \quad \text{where } |L(A_j) - L(A_R)| < \alpha_j,$$
$$A_R \in A(E) \vee A(D) \tag{16}$$

Each of the responding agents, A_R, receives a stimulation signal with different intensities. This intensity of a stimulation signal depends on two factors: (i) the stimulation signal of T_i, i.e., δ_i, and (ii) the distance between A_R and T_i, i.e., d_{iR}

Table 3
Functions that define the cooperation algorithm

AIS agent architecture (Individual level)
Activation threshold
AIS-based behavioral model (Collective level)
Cooperate behavior
Idle behavior
Request behavior
Reply behavior

$$W_{iR} = \frac{\delta_i}{d_{iR}}, \quad \forall A_R \in A'_j \tag{17}$$

A_R with the *Reply* behavior checks if it is qualified to participate in the cooperative task, T_i, by the activation threshold. A_R compares its activation index, W_{iR}, with the activation threshold, Γ_i, such that

$$T_i = \begin{cases} \mathit{TRUE} & \text{if } W_{iR} > \Gamma_i \\ \mathit{FALSE} & \text{if } W_{iR} < \Gamma_i \end{cases} \tag{18}$$

A_R is qualified to participate in T_i if its activation index is greater than the activation threshold. That is, when $T_i = \mathit{TRUE}$, A_R will be activated and join the cooperative task with the cooperate behavior. On the other hand, if $T_i = \mathit{FALSE}$, A_R will be suppressed and will start a new operational cycle by looking for new tasks with the Explore behavior.

5. Automated material handling systems

The performance and effectiveness of the AIS-based control framework is demonstrated through a case study of an automated material handing system. The case study involves material handling operations by a fleet of automated guided vehicles (AGVs) in a distribution center. An AGV is a typical transport component utilized in a distribution center or warehouse, which offers a high degree of flexibility in transporting material and interacting with plant equipment and personnel (Bohlander, 1999). Many research studies (Bakkalbasi, Gong, Goetschalckz, & McGinnis, 1989; Chevalier, Pochet, & Talbot, 2001; Hammond, 1986; Schilling, Arteche, Garbajosa, & Mayerhofer, 1997; Tsumura, 1994; Wee & Moorthy, 2000) suggested that AGVs are crucial components to facilitate and optimize an automated material handling system. There are a number of flexibilities offer by an AGV system, such as, diversity of vehicle types, route simplification between processes within complicated networks, and the ability to program and retrofit with new tooling to deal with diverse industrial needs (Bohlander, 1999).

Although there are numerous sophisticated AGVs available, many existing automated warehouses that deploy AGVs use a centralized or hierarchical control paradigm (Arora, Raina, & Mittel, 2001; Maekawa, Yamamoto, Tanaka, Ida, & Hibino, 1999; Ottjes & Hogendoorn, 1996; Prasad & Rangaswami, 1998). Such controls are integrated with the rest of the material handling system under which AGVs are coordinated by some form of central controller. In this case, AGVs are operated with a number of limitations. For example, they require various kinds of guidance for navigation, means of communication to transmit information between AGVs, and well-organized jobs definition generated during system planning stages. With these requirements, AGV-based material handling systems cannot be regarded as fully autonomous. To achieve a fully automated system for material handling operations, an improved control framework should be implemented. A set of functions, including dispatching of material handling tasks, specifying individual AGV behaviors, controlling information exchange between AGVs, and accomplishing delivery tasks should be included in the control framework. The necessity of these requirements has motivated the adoption of an AIS-based control framework in such distributed material handling systems.

By employing the AIS-based cooperative control, individual AGV with unique behaviors and capabilities can be deployed through cooperation and information exchanges with one another. We assumed that an AGV is able to execute different responses through the perception of its changing environment. The highly distributed and adaptive properties of the AIS-based control framework are therefore adapted to manage, coordinate and schedule such fleet of AGVs. As such, an intelligent multiagent and self-organizing material handling system that is robust and able to learn to achieve goals can be achieved.

In the following simulation study, AGVs represent AIS agents, and material handling operations are the tasks. The mission of the AIS agents is to search and complete all the tasks located in the workplace. This control framework is implemented with MATLAB and a simulation platform is developed to study the performance of the control framework through the performance of material handling operations. The performance of the AIS-based control framework is studied under the three cooperative domains.

6. Simulation study

The simulation study aims at evaluating the coordination and performance of the AIS-based control framework through the implementation of an automated material handling system. The AIS agents carry out material handling operations of searching and handling different types of tasks located in a simulated environment. A 50×50 unit square workplace is used in the simulation study. Two initial configurations of the agents depot are adopted, namely, (i) the Center depot where all agents are initially placed at the center of the workplace; and (ii) the Edge depots where equal numbers of agents are separately located at four different depots located along the edge of the workplace. The layout of the simulated warehouse is depicted in Fig. 3.

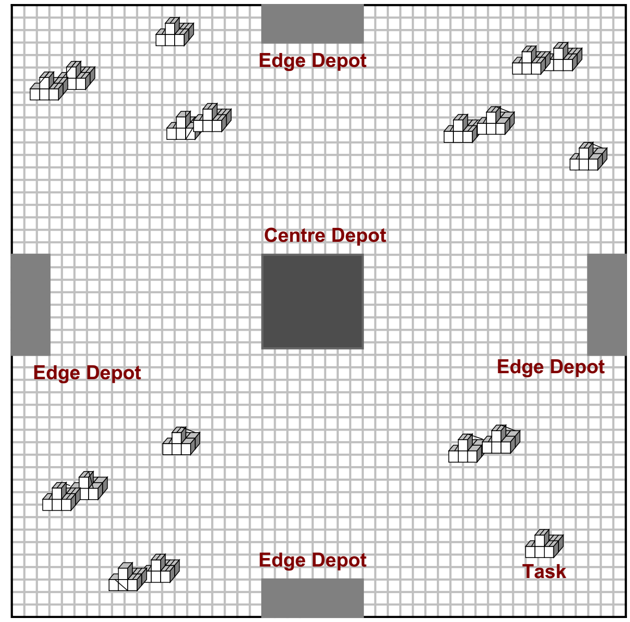

Fig. 3. An illustration of the layout of the workplace.

The AIS-based control paradigm is fully distributed where no supervisors or leaders are defined. AIS agents are allowed to move freely within the workplace and they have the ability to obtain information about the environment within their sensory range while they are exploring the environment and exchange information with other agents that are in close proximity defined by the communication range. In the simulation study, it is assumed that AIS agents are able to sense and communicate in eight discrete directions (Sectors Xi, $i = 1, 2, 3, \ldots, 8$) as shown in Fig. 4.

Material handling tasks defined in this study require either a single agent or a group of agents to handle. The control logic that describes the operation of the control algorithm is defined. Fig. 5 defines the control logic of the AIS-based control framework and Fig. 6 defines the decision logic of individual AIS agents in task handling. The state transition diagram of Fig. 6 specifies the rules adopted by an AIS agent in accomplishing tasks at different complexity levels.

The main objective of this case study is to demonstrate how coordination enhances the overall efficiency of a multiagent system based on the AIS-based paradigm. In view of this, the explicit handling of tasks is not within the scope of this study and the execution of these tasks is therefore not considered. Nonetheless, the complexities of these tasks are crucial for agents in making their decisions. Such complexities that represent different types of tasks are repre-

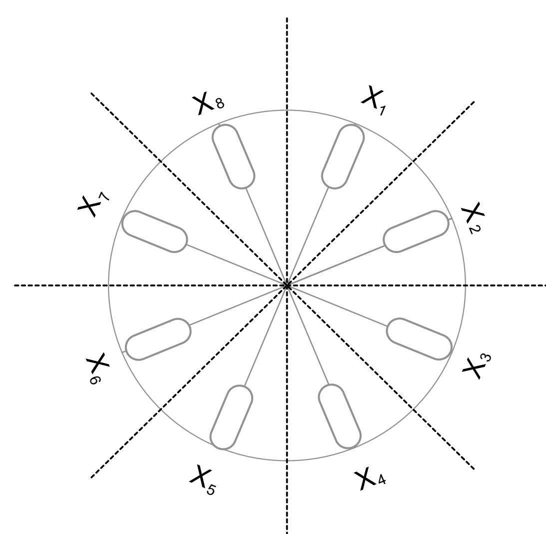

Fig. 4. The sensing and communication sectors of an AIS agent.

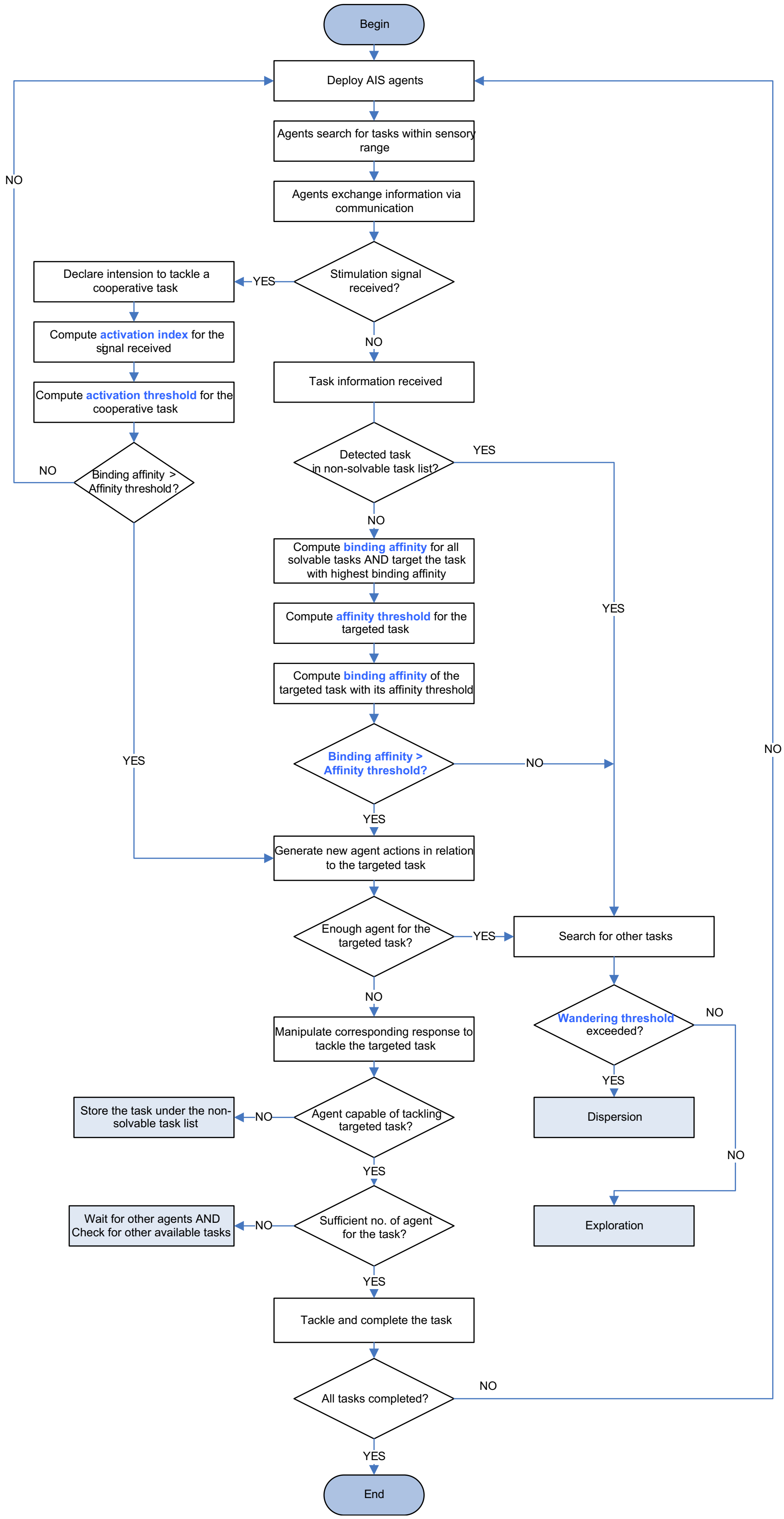

Fig. 5. The control logic of the AIS-based control framework.

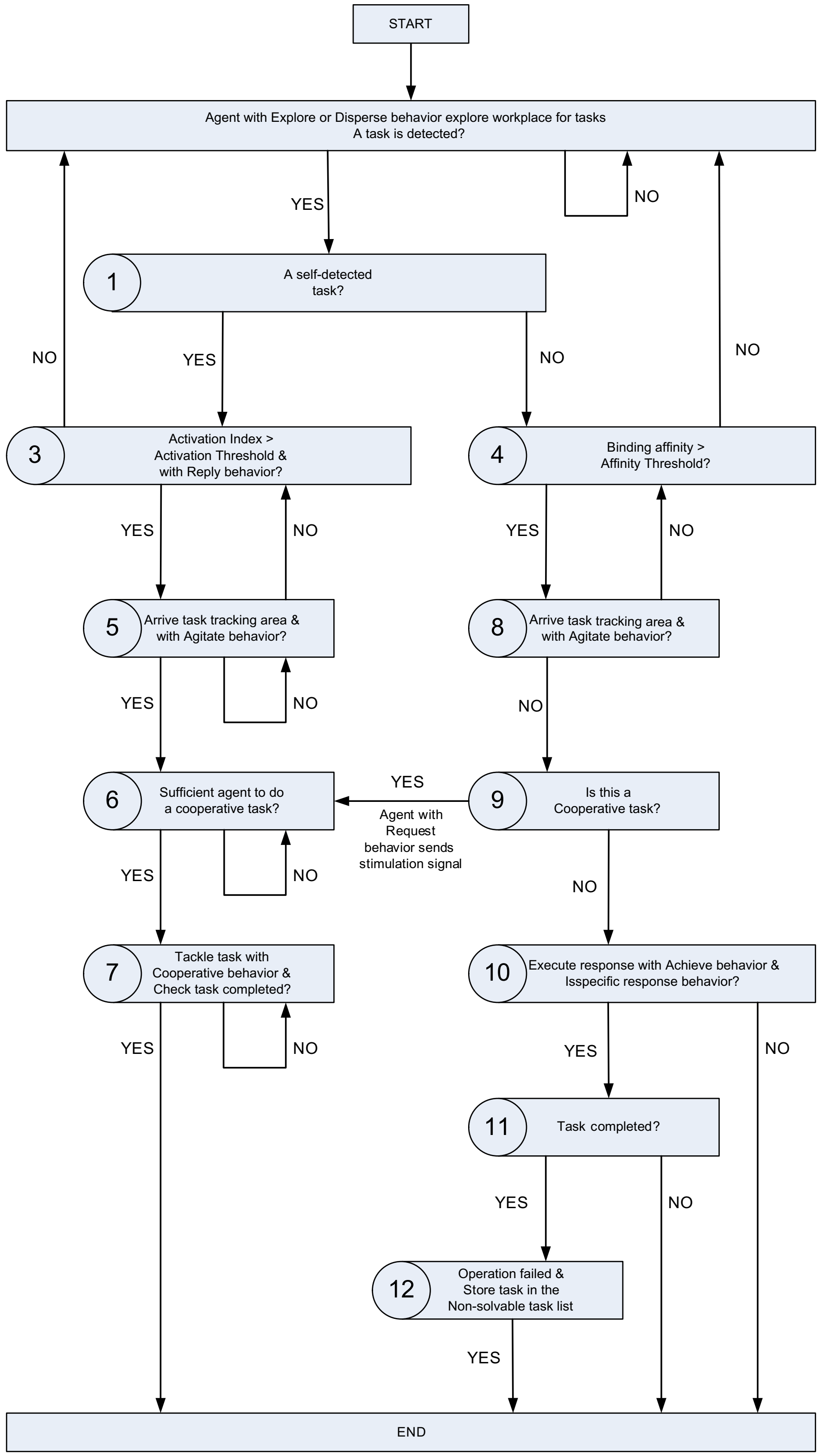

Fig. 6. A state transition diagram defining the decision logic of an AIS agent.

sented by their corresponding complexity chains by which specificity matching and binding affinity between tasks and agents are evaluated.

A simulation is said to be completed when agents have accomplished all the tasks in the workplace. As initiating agents will become idle when they are waiting for help, and in the case when the number of tasks is greater than the number of agents, a deadlock is resulted when all the agents have attached to different tasks and waiting for help. As such, a condition is imposed to limit the idling time for initiating agents, i.e., an initiating agent will evoke stimulation signals and wait for assistance within a fixed period of time. After that, if no one has replied to the signals, the initiating agent will abandon the cooperative task and search for other tasks. In this case study, the duration of idling time is set to 10 time steps.

7. Results and discussion

In the simulation study, a group of AIS-agents having the same capability is deployed to tackle ten tasks with the same complexity that are randomly distributed in the workplace. To highlight the cooperative activities among AIS agents, a constraint is imposed such that a group of four agents is required to handle the cooperative tasks. In order for a task to be satisfactorily handled by four agents, the agents have to occupy four Task Handling Locations that are allocated at the perimeter of the task tackling area as depicted in Fig. 7.

The decision for an agent to move to an unoccupied Task Handling Location depends on whether the nearest Task Handling Location has already been occupied by another agent. This is achieved by an AIS agent moving into a nearest Checkpoint, which is defined as the location that is one step further away from a Task Handling Location (Fig. 7). The outer perimeter connecting all the Checkpoints is defined as the Ring. Once an agent has reached the Ring, it then moves in a clockwise direction to check for any vacant Task Handling Locations.

Based on these assumptions, the performance of the AIS-based behavioral model is evaluated using three cases with different conditions as summarized in Table 4. Case I includes tasks with the same complexity level that can be tackled with basic agent's capabilities. In Case II, tasks are more complicated and have different complexity levels. These tasks have to be completed by specific responses with which agents need to acquire new capabilities through capability manipulation. Case III demonstrates the regulation of agents' behaviors in dealing with cooperative tasks. In this case, all tasks require a group of four agents to complete. The significance of the exploration, achievement, and cooperation domains and the impacts of the agents' behaviors on the overall performance of the AIS-based material handling system are examined with regards to their action performed in completing the ten defined tasks. By counting the specific actions taken by different numbers of AIS agents in tacking these tasks, the performance of the overall system can be deduced.

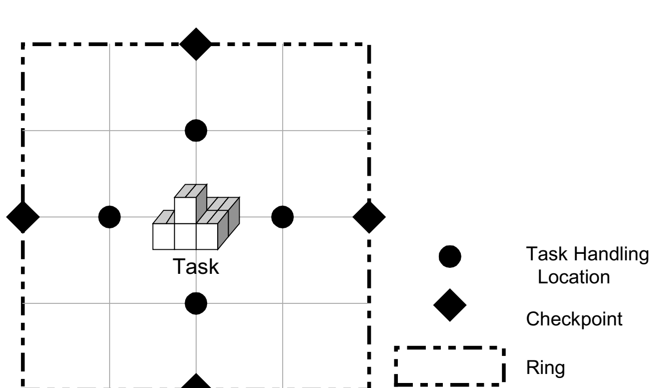

Fig. 7. An illustration of the task tackling area.

Table 4
The three cases with associated input parameters in the study of the AIS-based behavioral model

Cases	Task nature	Capability	Response
I	Basic tasks	Basic capability	Non-specific
II	Complex tasks	Compound capability	Specific or acquired
III	Cooperative tasks	Basic capability	Non-specific

7.1. Exploration domain

According to the AIS-based behavioral model (Ishiguro et al., 1998), *Explore* and *Disperse* are the two primitive behaviors that govern the exploration activities in the exploration domain. Fig. 8 shows the relationship between the numbers of activation of these two behaviors under the three cases. The average number of actions performed per agent is recorded to observe the frequencies of the *Explore* and *Disperse* behaviors on exploration activities when different number of agents is dealing with different types of tasks.

A direct proportional relationship is found in Cases I and II between (i) the *Explore* and *Disperse* behaviors, and (ii) *Disperse* behavior with the number of agents deployed. This observation is made when no cooperative task are present. As the number of agent increases, dispersion takes place more frequently. Hence, the number of occurrences of the *Explore* behavior decreases when the number of agents and *Disperse* behavior increase.

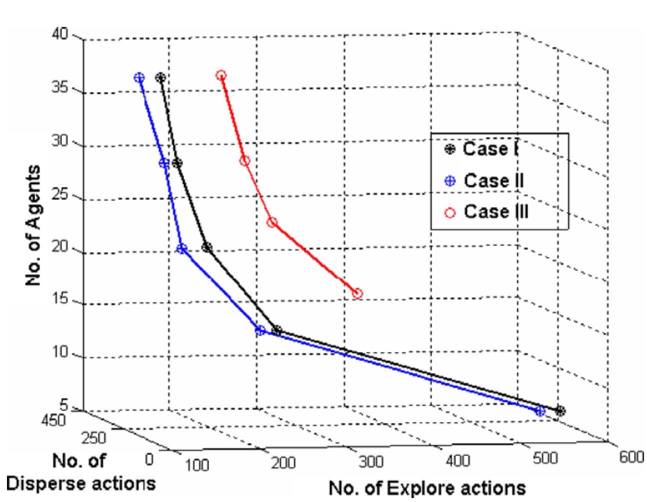

Fig. 8. Relation of disperse and explore behaviors in the exploration domain.

As cooperation is required in Case III, the concentration of agents in the same proximity is much higher. In this case, dispersion helps to scatter the agents once they have completed a cooperative task in order to maintain the efficiency of task exploration. The occurrence of the *Disperse* behavior in Case III is therefore much higher than the *Explore* behavior even with a small number of agents deployed. It can be concluded that the *Disperse* behavior is a crucial behavior adopted by the agents to avoid overcrowding and allow efficient exploration activities.

7.2. Achievement domain

In achieving goals, AIS agents act aggressively and adopt the *Agitate* behavior once they have targeted at a task. The *Achieve* behavior will then direct agents to complete the task. The average number of behavior activated per AIS agent is shown in Fig. 9. The figure shows how agents regulate their behavior in achieving different types of tasks and how often an agitated agent can successfully complete its targeted task under the three different cases.

In Cases I and II, agents achieve tasks only through responses manipulation. A straightforward sequence of activities: (i) being agitated when a task is identified, (ii) achieving the targeted task, and (iii) completing the task is observed. Hence, the results for Cases I and II share a similar pattern where some of the data are almost identical. With an increasing number of agents deployed, the numbers of *Achieve* and *Agitate* behaviors that each agent adopt decreases. This is mainly due to an increase in workforce where the number of tasks completed per agent is reduced. Moreover, the average number of occurrence of *Agitate* and *Achieve* behaviors is proportional to each other. This implies that the task achievement rate for non-cooperative task depends on the ability of an agent to search for tasks since the agent will become agitated once a task is found.

Case III on the other hand requires agent cooperation; therefore the number of *Agitate* behavior that an agent adopts is much greater than the number of *Achieve* behavior. As a group of agents is required to handle one task, agents will become agitated more frequently and thus the number of adoption of the *Agitate* behavior increases significantly. This also leads to a drop in the task achievement rate per agent, and hence the average adoption of the *Achieve* behavior in Case III is much lower when compared to Cases I and II.

7.3. Cooperation domain

As defined by the behavioral model, *Reply*, *Request*, *Idle* and *Cooperate* are the primitive behaviors that give rise to cooperative activities. Fig. 10 shows the relationships between two pairs of behaviors: (i) *Request* with *Reply* behaviors; and (ii) *Idle* with *Cooperate* behaviors with different number of agents present under Case III where cooperative tasks are present.

The two graphs in Fig. 10 show very similar results. An agent that is tackling a task that required joint effort will become idle if the number of AIS agent is not enough. In the meantime, the agent that has first targeted a task will send stimulation signals to request for assistance. The average numbers of behavior adoption for *Idle* and *Request* are therefore almost the same. On the other hand, the average adoption rate of the *Reply* behavior is greater than the average adoption rate of the *Cooperate* behavior. This is because agents who received a stimulation signal requesting for help during exploration will reply to the signal anyhow. After that, the agents need to evaluate their capability to participate in the cooperative task by the evaluation of the activation threshold and only qualified agents will be activated to participate in the cooperative task. The activated agents with the *Cooperate* behavior move towards

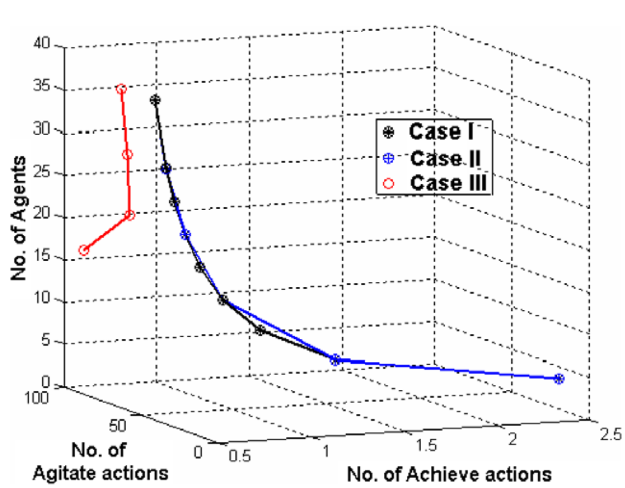

Fig. 9. Relation of agitate and Achieve behaviors in the achievement domain.

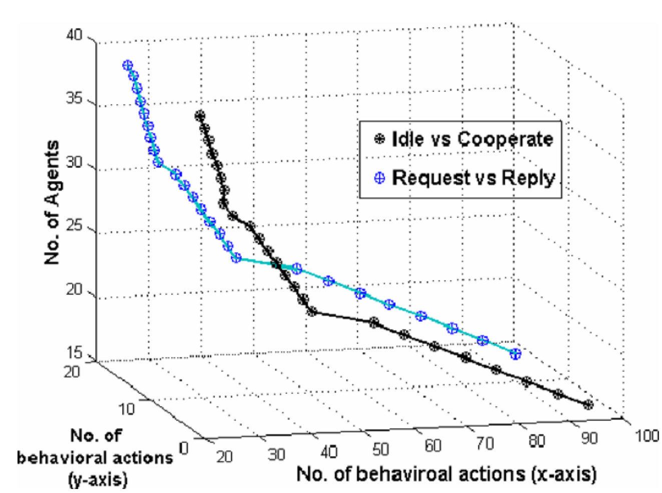

Fig. 10. Relation of agitate and Achieve behaviors in the cooperation domain.

the cooperative task and tackle it with other agents. Since a reply to a stimulation signal does not imply a successful cooperation, the average adoption rate of the *Reply* behavior is therefore much higher than the *Cooperate* behavior.

A reduction of idle agents requesting for help is resulted when the number of agents increases (Fig. 10). There is a noticeable difference in the average number of occurrences of both *Idle* and *Request* behaviors. For the specific workplace defined in our study, an average stimulation evoked by an initiating agent has declined significantly when 22 agents are deployed. This indicates the optimal number of agents necessary for effective cooperation in the simulated workplace. According to this result, a significant improvement is observed when the number of agents employed is greater than 24. A steady improvement is also obtained beyond the optimal point which is mainly due to a constant increase of workforce. It can be concluded that the AIS-based cooperative control model allows the evaluation of the optimal resources, in this case the number of agents deployed, to attain effective cooperation. Such results help to prevent shortages or wastage of resources which hinders the system overall performance.

8. Conclusion

This paper presented a cooperative control model for AIS-based multiagent system. The model controls the collective behaviors of AIS agents by regulating the activities of individual agents. Such cooperative control is achieved by the evaluation of corresponding threshold measures together with the activation of activities under the AIS behavioral model. The threshold measures and the collective behavioral model are being structured under three domains, namely, the exploration, achievement and cooperation domains, which are governed by associated algorithms that are presented in this paper. The performance and characteristics of the cooperative control model was studied with an implementation of a distributed material handling system. Simulation studies were carried out to investigate the regulating capabilities through the evaluation of the threshold measures under the three domains. Results of the simulations shown that agent's activities are being regulated to avoid overcrowding, to cooperate with one another and to tackle tasks. This further establishes the distributive nature of the AIS-based control model where a centralized coordination is not required even for cooperative activities. With the introduction of the cooperative control model, it is seen that a new computation paradigm can be realized for the efficient decentralized control of multiagent systems.

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