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AN AIS-BASED OPTIMAL CONTROL FRAMEWORK FOR LONGEVITY AND TASK ACHIEVEMENT OF MULTI-ROBOT SYSTEMS

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Abstract. Extending the longevity of autonomous agent system in real life application is a difficult task, especially in applications which require continuous high system performance. This paper presents a novel decentralized balancing controlling architecture for longevity and achievement in multi-agent robot systems based on several artificial immune systems (AIS) designs and principles. Simulation experiments have verified the proposed architecture has good capability to efficiently minimize the trade-off in system achievement while maintaining system sustainability, even in very demanding situations.

1. **Introduction.** Being a new paradigm for organizing Artificial Intelligent (AI) applications, in the past decade, there are many researches being done on multi-agent system (MAS) [1, 2, 3, 17, 18, 19]. MAS has already demonstrated its flexibility in tackling complex non-linear problems, such as data mining [32, 39], decision mining [34], intrusion protection [27, 33], linguistic evolution [5], material handling [16, 22], traffic control [4], robot coordination [29, 39], etc. Many complex real-life cooperative systems can benefit from MAS control, including automated production systems, modern distribution centres and warehouses, port container terminals and transportation systems that are indispensable in modern logistics businesses.

In MAS based robotic system, also known as multi-robot system (MRS), there are usually a team of autonomous robot agents which are operated individually but are also coordinated to target some team achievements. Therefore, the overall achievements of MRS are directly affected by the number of usable robot agents inside the system and agent failures should be prevented in order to uphold system reliability. Unfortunately, due to unforeseen circumstances happened in real situation, the longevity of MRS usually requires sophisticated mechanisms to maintain [10, 11, 25, 28]. When failure prevention and recovery mechanisms applied in place to maintain the number of usable agent in system, the additional resources spending on agent maintenances, however, do adversely introduce significant trade-off to the

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overall system achievement and performance in terms of efficiency and effectiveness. The way for minimizing the trade-off between longevity and achievement of MRS is crucial for future development of MRS.

To tackle the mentioned problem, this paper presents a novel decentralized adaptive balancing control architecture which is motivated from biological theory of immunology to control the recovery process of multiple agent nodes and optimize the trade-off between overall achievement and longevity of MRS. Simulation studies were made to verify its validity on balancing the resources being use to maintain system sustainability and performance.

2. **Artificial immune system.** Inside our body, one of the most complex and self-maintained cooperative defence system in the world - the Human Immune System (HIS), which co-operate trillions of immune cells to rapidly response and protecting us from unpredictable invasion and attack of foreign pathogens such as bacteria and virus [8, 12]. The HIS involves two kind of immune response : innate immune response and adaptive immune response [24]. Innate immune response serves as the first barrier which prevents pathogens entering our body and minimizes the likelihood of being infected; while the adaptive immune response serves as the second barrier which activates if pathogens evade from innate immune response and help us recover from infection by producing antibodies for fight pathogens [31]. By extracting the concepts behind those sophisticated cooperative mechanisms in HIS as metaphors and engineering paradigms, immune-based AI system can be built for solving different real problems. Those systems using these immune-based paradigms are known as Artificial Immune Systems (AIS).

The theoretical framework of AIS has been broadly studied in the field of Artificial Intelligence (AI) [8, 9, 12, 15, 37, 38]. Several studies concerning distributed multi-agent system control have been carried out previously and shown the AIS-based control framework having desirable performance and flexibility for multi-agent coordination. Dasgupta [7] proposed a general framework for multi-agent decision support system; Lau & Wong [21] developed a distributed multi-agent control framework to effectively control a group of agents with different capabilities; Lu & Lau [23] created a real-time cooperative control framework for networked multi-agent systems.

3. **Extending longevity with AIS-based control.** Inspiring from the distributed self-organized property of human immune systems [13, 20] , immune network theory [14], danger theory [26] and other earlier studies [7, 21, 23], we developed an Immune-Based Cooperative Sustainment Framework (IBCSF) [6] based on the mechanism between innate response and adaptive response. Through a two-level behaviour control model as the core of the design with the concept of sustainment (Figure 1), it adopts the immunity-based regulation mechanisms to control when the system restores the failed agent nodes and extends the system longevity in situation where exists some unpredictable agent failure.

In our immune system, innate immune response serves as the first barrier which tries to stop pathogens entering our body and minimizes the chance of being infected; while adaptive immune response activates if pathogens evade from innate response and produces antibodies to fight and recover from infection [31]. In IBCSF, there are also two lines of defence which are similar to HIS. Self sustain response

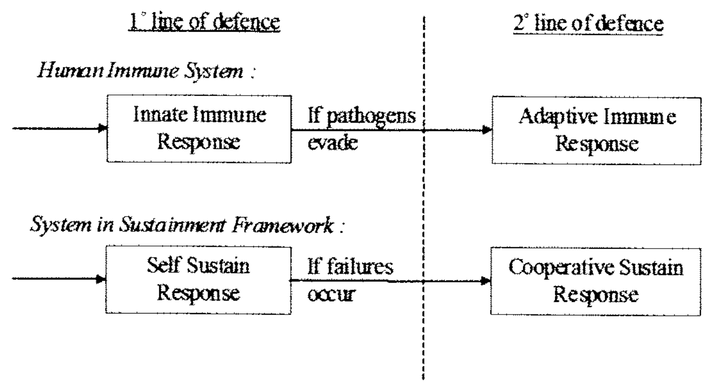

FIGURE 1. The two-level defence mechanism in HIS and IBCSF [6]

serves as the first barrier to minimize the chance of agents failure while cooperative sustain response triggers when there are agent failures occurred and helps the system to recover.

The reasons of having two levels of defence are that the two different responses have their own strengeths and we cannot depend on one level only. Neither one kind of responses will be sufficient to protect the system alone. Even only one pathogen is evaded from the innate response, we may still suffer from serious illness. On the other hand, we do not want to stop the innate immune response and have the adaptive immune response to fight for all the pathogens because activating adaptive immune response may introduce some side-effects, such as fever - a kind of undesirable symptoms.

The design of the two-level sustainment responses in IBCSF shares the same characteristics with innate and adaptive response in HIS as mentioned above.

4. **AIS-based adaptive balancing architecture.** Based on the concept of IBCSF, we have extended the framework and develop new adaptive Longevity and Achievement Balancing Control Architecture (LABCA) for MRS. As depicted in Figure 2, there are two layers of concurrent adoptive controls in the proposed LABC architecture, namely adoptive achievement control layer and adoptive longevity control layer. These two control mechanisms are operated simultaneously inside each individual agent and are connected through an artificial immune system - network of antibodies and cytokines. The behaviors of each agent are adjusted from time to time based on expected system throughput, individual agent's perceptions, individual agent's experiences and co-stimulations between other agents, to allow the system to keep a reasonable achievement rate while maintaining the system longevity in different dynamic environments.

The two controls are separated because they serve different purposes and behave in opposite way.

The adaptive achievement control targets ordinary tasks, which is responsible to perform system designed objective, such as production, delivery, patrol, etc. The control can be further divided into individual level and cooperative level, according to the number of agents involved in the behaviours.

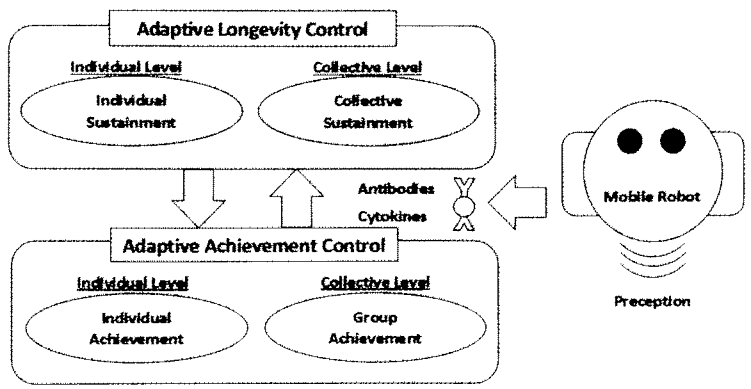

FIGURE 2. Design of the Longevity and Achievement Balancing Architecture (LABCA)

Above this, we have a layer called adaptive longevity control, which is responsible for sustainment operations that preserve the system life. Inside this control layer, there are two further levels of agent failure detection and agent restoring behavioral controls for reducing the amount of effort and resource required to keep the agents alive: 1) Collective Sustainment, which provides the ability for agents to recognize system failures and solve problems that beyond the capabilities of any individual agent; 2) Individual Sustainment, which provides the ability for individual agent to recognize problems itself and try to solve those problems before it goes beyond its own capabilities.

4.1. **Concept of sustainment.** The concept of sustainment is crucial for building the LABCA. Sustainment is defined as the necessary operation that is used to guard and increase the system sustainability, such that the system maintain its functions and remain productive for a longer time. Its meaning is different from maintenance, as sustainment includes maintenance, and not limited to repairing operations and replacement of components. Rescheduling processes and reallocating resources are also considered as a kind of sustainment because they help to extend the system life in different ways. In this paper, sustainment response refers to a strategic sustainment operation series.

Sustainment response is the most important concept in the proposed architecture and it remains our major concern in the operation to prevent unpredictable system failure. The two levels of sustainment response: Individual Sustainment Response and Collective Sustainment Response in LABCA form indispensable defences for MRS to recover from different degrees of agent failures and play an important role in maintaining the balance between system performance and sustainability. The key factors and considerations of individual sustain response and collective sustain response will be explained in details in the following section.

Individual sustainment. Individual sustainment is the self-governing protection strategic operations performed by individual agents. While innate response stops infection in HIS, individual sustainment is the first barrier of protection mechanism which stops an agent from failure. An example of individual sustainment action can be a resolution to stop partially damaged agent from its normal function and undergo repairing progress before the agent becomes completely malfunctioning (See Figure 3).

The key factors in the adaptive sustainment control are how and when the individual sustainment operation should be triggered.

Individual sustainment are considered as a less expensive sustainment operation, as the agents are still in a functional state and are able to trigger individual sustainment response by themselves.

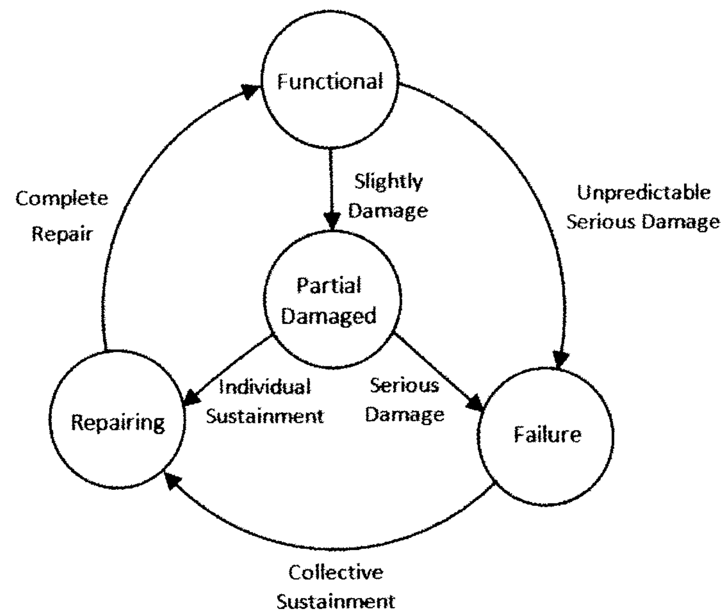

FIGURE 3. Different Stages of Agent in LABCA

Collective sustainment. Collective Sustainment is the group strategic protection operations performed by several agents, aiming to make the system survive longer in environments with uncertain factors leading to serious agent failures. This inter-preservation strategy starts whenever agent failure occurs in the system and helps repairing the failed agents or take over the task of the failed agents. A typical example of collective sustainment action can be a rescue action, such as a functioning agent discovers a failed agent and sends it back to the repair station.

Collective sustainment operations are considered as the costliest sustainment operation. As the failed agent is not able to trigger individual sustainment, the operation requires the involvement of other functioning agents. Because the functioning agents are spending time and efforts to undergo maintenance instead of performing useful work, collective sustainment usually effect in reduce the effective performance of the system at a particular period of time.

The key considerations in the adaptive sustainment control are how collective sustainment control can be highly adaptive to target the uncertainly failure factors and to balance between system performance and sustainability.

Immune System	**AIS-based LABC Architecture**
Self	Agents
Non-self	Tasks, Failed Agents
Anti-body	Pair of Conditions with Strategic Behaviours
Antigen	Set of Conditions in the Environment
Antigen Presenting Cell (APC)	Sustainment Evaluator
Innate Response	Individual Sustainment Behaviour
Adaptive Response	Collective Sustainment Behaviour
Stimulus	Agent Failure
Suppression	Agent Recovery

TABLE 1. Relationships between the LABCA and the immune system

4.2. **Operational scheme.** In HIS, antibodies are circulate through the blood and lymph systems in our body to respond with antigens in a distributed coop-erative manner [24]. On the surface of antibodies, there are some special binding areas known as paratopes and idiotypes. Paratopes are structures that allow the antibodies to identify the antigen of foreign pathogen (non-self) and react corre-spondingly; idiotypes are structures that allow co-stimulation between antibodies to regulate immune response [35]. The mappings between immune system and the LABCA are shown in Table 1.

The control of sustainment operations and behaviours are done using suppression and stimulation mechanism based on immune network theory [32]. During normal operation (See Figure 4), the condition around the system environment is perceived by the agents as perceptions through different detectors and sensors. The sustain-ment evaluator would then process the perceptions and evaluate the current system situation. After generating conception about the situation, the signal would then presented to the sustainment reactor which stimulates or suppress the actions that agents decide to make.

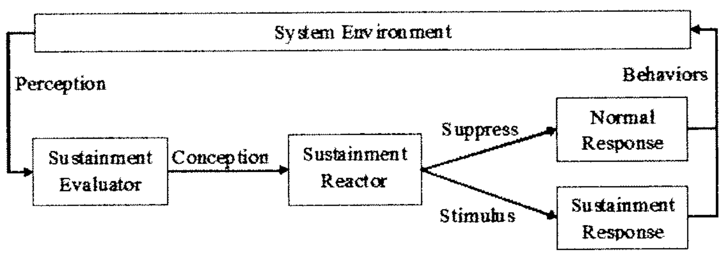

FIGURE 4. Flow of operation from perception to behaviours

Inside the sustainment reactor, the behavioural decision making mechanism are formulated by two anti-bodies, the Normal Behaviour Antibody, N-Cell, and Sus-tainment Behaviour Antibody, S-Cell. Conceptions of an agent are modelled as the paratopes which are the combinations of situations that can be detected by the sen-sors of an agent. Once an agent detected a specific signal from the environment, the intake conception set would be matched with the set of antibodies in the reactor.

Affinity is calculated by the number of conceptions matched. Details structure of antibodies can be found in Figure 5.

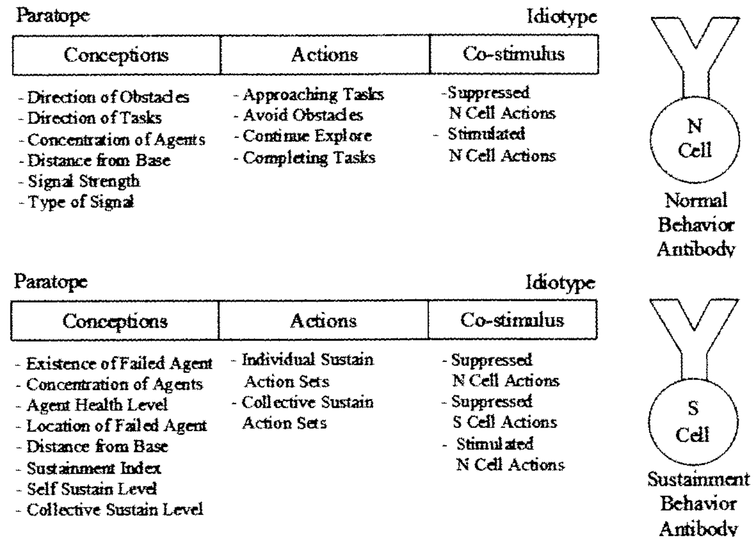

FIGURE 5. Design of N Cell and S Cell

4.3. **Dynamics.** To determine when the individual sustainment operation should be triggered by an agent, the current health (H_a) of agent a is compared with its Self Sustainment Threshold SS_a^T , which is formulated in the follow Equation 1:

$$SS_a^T = \frac{t_a^R \times \bar{d}_a}{SS_a^L} \tag{1}$$

$$SS_a^L = \frac{t_a^W}{t_a^D + C} \tag{2}$$

where $\bar{d}_a$ is the average damage rate suffering by Agent a per unit time according to the history of Agent a, t_a^R is the estimated time required to wait before Agent a can receive any maintenance, SS_a^L is the Self Sustainment Level of Agent a that is calculate by Equation 2, where t_a^D is the accumulated downtime of Agent a and t_a^D is the accumulated working time of Agent a.

The Self Sustainment Level SS_a^L reflects the sustainability of Agent a, where $0 \leq SS_a^L \leq 1$. When the sustainability of an agent is high, the value approaches 1 and it drops as sustainability drops.

If $H_a > SS_a^T$, individual sustain behaviours are suppressed, otherwise individual sustain behaviours are stimulated to restore the health of an agent before complete failure of agent.

Considering an Agent a discovering two tasks at the same time, one is involves an ordinary mission to produce a product using one cycle of time; the other is a rescue mission to repair a failed Agent b. If Agent a choose the former one, the production performance of the MRS is maintained, the sustainability of the system however would suffers; if Agent a chooses the later mission, the sustainability of the MRS is maintained, the productivity however suffers. In order to balance the system performance and sustainability, we can control the participation level of agents in collective sustainment operations by calculating the level of Collective Sustainment CS^L_a using Equation 3:

$$CS^L_a = \frac{A^F_a}{A^W_a \times (SS^L_a)^{N^F_a}} \tag{3}$$

where A^F_a is the number of failed agents detected by Agent a, is the number of working agents detected by Agent a, N^F_a is the number of failure encountered by Agent a according to its own history.

The level of collective sustainment formulates the needs of collective sustainment operations for Agent a at a particular moment and to determine the chance of Agent a to perform the sustainment actions. If $CS^L_a \geq 1$, that means collective sustainment is needed, priority for collective sustainment operation is high. If CS^L_a trends to zero, this means the priority for collective sustainment operation is low and the agent is relief to perform other tasks first.

5. **Experiment and result.** To verify and confirm the validity of our proposed architecture, we applied it to an autonomous multi-robot system and examined the system in Player/stage [30] simulation environments(see Figure 6),. In the experiments, there are 10 robot agents working in a distribution centre. Their job is to move cargos from inbound platforms to specific outbound platforms. Cargos arrive in random interval with random amount. Energy of robots is consumed according to a random rate per hour. There is a charging station inside the distribution centre for robots to recharge themselves. If the robot runs out of energy, it will need other agents to assist in charging, this as a result will reduce the overall throughput.

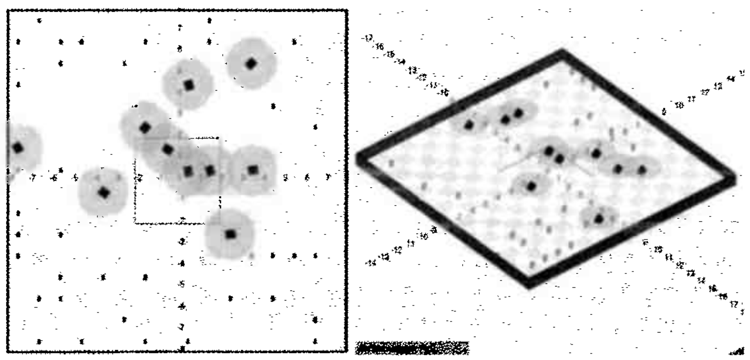

FIGURE 6. Simulation of 10 robot agents working in distribution centre with stochastic energy consumption. (Left : Top View; Right : 3D View)

The individual sustainment operation in this experiment is bringing agent (robot) back to the charging station in the middle of the distribution centre before it completely out-of-energy. Correspondingly, the collective sustainment operation is sending out-of-energy agents back to charging station by other agents. The purpose of the experiment is to find out whether the LABCA can help to minimizing the trade-off in system achievement and longevity by automatically adjusting the time

interval between each recharging, the number of out-of-energy robots leave behind and the time for carrying out rescue action.

Since the time required for a robot to return to the charging station is proportional to its distance from the base against its speed of the agent. Equation 1 can be rewritten as:

$$SS^T_a = \frac{l_a \times \bar{d}_a}{\bar{v}_a \times SS^L_a} \tag{4}$$

where l_a is the distance of Agent a from base area and $\bar{v}_a$ is the average velocity of Agent a.

The LABCA has been applied to four different robot setups with mean energy consumption rate of 5%, 10%, 15% and 25% per hour respectively and the distribution centre is assumed to be operated a week with 24 hours a day. The experimental results of the LABCA are given in Figure 7 and Figure 8, where results are compared to two control systems A and B.

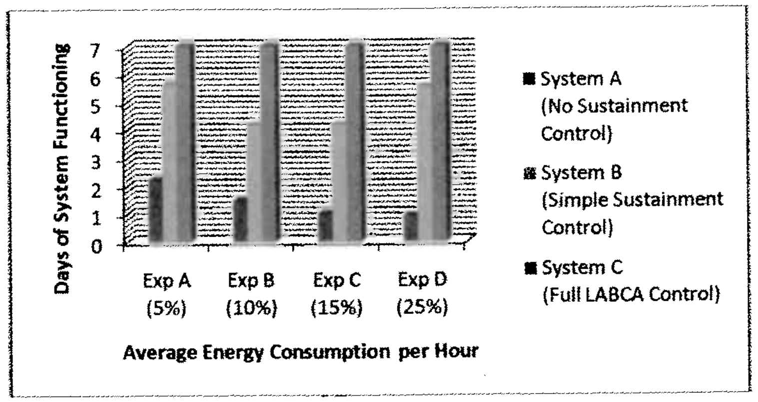

FIGURE 7. Comparison of average longevity of robot systems with different energy consumptions

Control system A has no sustainment control applied. Robots in system A focus on cargo delivery rather than self sustaining, they go to the recharging station only when they are passing nearby the station. Therefore, in all experiment setups, system A stopped working within 2.5 days; Control system B has simple sustainment control, which only applied the individual sustainment Equations 1 and 2 but does not include Equation 3 for collective sustainment. As a result, the system life of system B is extended from two to six days in different setups but still not able to last for a week; Only System C which applied the full proposed LABCA control is still functioning at the end of the week until the experiments ended. This clearly shows the effectiveness of full LABCA in extending MRS longevity.

More importantly, when comparing the useful agent available throughout the three systems (see Figure 8), without collective sustainment which control the participation level of agent in rescue operation, the sustainment control mechanisms do introduced overhead to the system, and the overall useful throughput of the system B becomes lower than the system A with no sustainment control. However, the full LABCA control mechanism helps to dramatically reduce the overhead and boost the overall performance of the system C. The result shows that the incorporation of the two levels LABCA is crucial for maintaining the overall achievement of MRS.

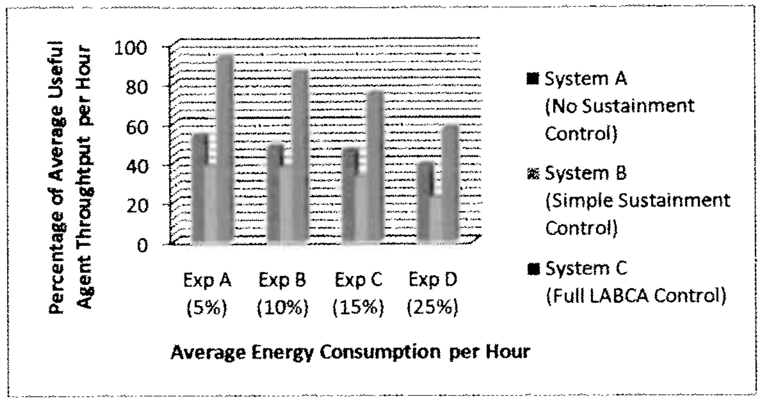

FIGURE 8. Comparison of average achievements of robot systems with different energy consumptions

6. **Conclusion and future works.** In this paper, we introduce a new collective adaptive Longevity and Achievement Balancing Control Architecture (LABCA) that is inspired from the human immune system. The performance of the control architecture is studied with a multi-robot system performing cooperative tasks in a simulated environment. Although the implementation of the proposed control architecture in the experimental study is rather simple, the result shows the capability of the control architecture to optimally balance the activities of multi-robot system achievement while maintaining system sustainability by automatically adjusting the time interval between each recharging, the number of out-of-energy robots left behind and the time to carry out rescue actions after agent failures detected in the system.

Currently, we are building an experimental system with physical robots for studying the architecture in real environments. We hope this architecture can be applied to solve various real problems in multi-agent systems.

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GLOBAL OPTIMIZATION VIA DIFFERENTIAL EVOLUTION WITH AUTOMATIC TERMINATION

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ABSTRACT. Evolutionary Algorithms (EAs) provide a very powerful tool for solving optimization problems. In the last decades, numerous studies have been focusing on improving the performance of EAs. However, there is a lack of studies that tackle the question of the termination criteria. Indeed, EAs still need termination criteria prespecified by the user. In this paper, we propose to combine the Differential Evolution (DE) method with novel elements, i.e., the "Gene Matrix" (GM), the "Space Decomposition" (SD) and "Space Rotation" (SR) mechanisms, in order to equip DE with an automatic termination criterion without resort to predefined conditions. We name this algorithm "Differential Evolution with Automatic Termination" (DEAT). Numerical experiments using a test bed of widely used benchmark functions in 10, 50 and 100 dimensions show the effectiveness of the proposed method.

1. **Introduction.** Differential Evolution (DE) is a very competitive evolutionary algorithm for solving real-parameter optimization problems that first appeared in 1995 in a technical report written by R. Storn and K. Price [19]. Since then, DE has attracted particular attention and yielded a significant number of research articles.

Practitioners particularly appreciate the relative simplicity to implement and efficiency for many optimization problems in real-world applications [17, 9, 22]. Another advantage of DE compared with other EAs is that the number of control parameters is very low (three for the classical DE, namely, the population size NP, the crossover rate CR and the scaling factor F). A number of papers in the literature extensively study the influence of these parameters on the performance of the algorithm [2].

As other EAs, DE is population-based and uses common features of EAs such as recombination and selection operators. However, one of the distinctive features of DE lies in the fact that it exploits the information about differences between trial solutions, the latter being identified as *parameter vectors*, to explore the search space. Basically, in DE, the mutation operator considers two parameter vectors and adds a weighted difference vector to create a third parameter vector. Different

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