# Research on Cooperative Control in Intelligent Agriculture Complex System

Ge Li, Yifei Chen, and Shangfeng Du

***Abstract*—Intelligent Agriculture (IA) system is a complex system featured by complexity, uncertainty and large time-delay, and all its subsystems need cooperation with feedbacks from each other so that the whole system's control targets could be achieved. Components of IA system are dispersed unities with independent control targets, it is proved that Multi-Agent technology for system modeling and control is a useful method with simplicity and validity. In this paper, we had tried to research the cooperative control for IA system with this method firstly, and the way of Q-learning was used in researching of multi-agent collaboration control inference rule. According to control needs of three kinds of strawberries planted in the same greenhouse, we had designed different control agents corresponding to each environment variables. Joint optimal solution among these factors had been achieved through global control optimizing by cooperation controller, and intelligent adjusting of whole system can be effectively realized.**

***Index Terms*—Intelligent agriculture (IA), complex system, reinforcement learning, cooperative control.**

## I. Content and Structure of Intelligent Agriculture

Definition of IA from the point of view of complex system cybernetics and intelligent control is actually blank at present. Based on control concepts, IA system is an integrated large-scale closed loop control system of various technologies [1]. According to reference [1], IA system based on large-scale system control must have the following two distinct characteristics: (1) Feedback Control. In this system, procedures from information presetting and processing, to signal acquisition and feedback should be in the closed loop frame. (2) Cooperative and Autonomous Control. The system's control module and model should have the capacity of self-adaptation, self-study, and active fault-tolerance.

Fig. 1 is the multi-level hierarchical model of IA system from reference [1]. In this system, subsystems respectively representing the pre-stage, mid-stage and post-stage of agriculture production system are designed at the micro level. The various subsystems are subject to regulations of their local controllers, and the macro harmonizing controller in the system observes the hierarchical information flow and figures out global optimization solution as given constraints to all local controllers by means of the Internet.

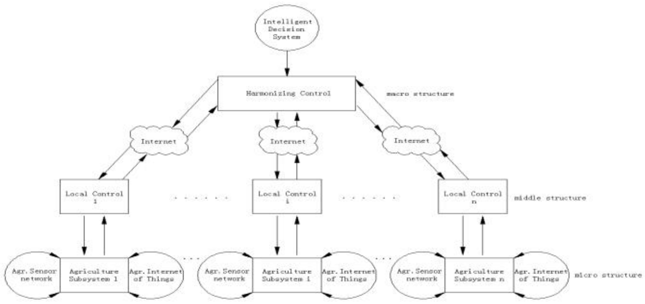


Fig. 1. Multi-level hierarchical model of IA system based on intelligent cybernetics of large-scale Systems.

## II. The General Method of Cooperative Control

Components of IA system are all dispersed unities with independent control targets, it is proved that Multi-Agent technology for system modeling and control is a useful method with simplicity and validity [2]. With greater flexibility and adaptability, the Multi-Agent approach removes dependence on accurate system model and is more suitable and effective for implementation and analysis of distributed systems [3]. This article designed multiple agents for agricultural subsystems and realized intelligent cooperation among them.

It's a very challenging and interesting subject to figure out a simple and effective way to achieve cooperation of Multi-Agent system and endow agents abilities to adapt to a dynamic environment. Through learning, agents can change their behaviors as well as their structures as response to changes in environment and finally realize global evolution. This paper discussed cooperation of multi-agent based on reinforcement learning [4]. In the environment of Markov Decision Process model, Agent learns an optimal behavior strategy to maximize an indicator function (i.e, the value function) [5].

According to reference [5], for the quadruple Markov decision process MD*P*=< *S*,*A*,*T*,*r* >, define a function *Q*: *S*×*A*→*R*, and formula is given as here:

$$Q_{t+1}(s_t, a_t^u) = r(s_t, a_t^u) + \gamma \max Q_t\,(s', a^{u'})$$

Use the optimal *Q* function to approximate the optimal value function *V**. Of which: S is an aggregate of finite states in random environment, A is a finite aggregate of agent actions, *T*: *S* × *A* → Δ (*S*) is the transition function between the states, *r*: *S* × *A* → *R* is the immediate reward function or expectation of a state-action pair , $\gamma$ ($0 \le \gamma < 1$) is the discount factor, *s*', $a^{u'}$ are respectively the next state vector and the corresponding joint action vector at the same iteration step *t*,

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policy $\pi$ describes agent' s options for actions under various states.

Since in a distributed multi-agent system, agent $i$ usually has no complete observation information about other agents, the Q-value table of full information will have to be projected and compressed as incomplete information of agent $i$ by $q^i(s,a^i)$ [6]. For each agent $i$ and iteration step t, there are iterative formula as following:

$$q_{t+1}(s_t, a_t^i) = \max\{q_t^i(s_t, a_t^i), r(s_t, a_t^u) + \gamma \max q_t(s', a^{i'})\}$$

The $q^i$ value table always holds the $q^i$ values of transitions that maximize agent's revenue, thus agent could choose the state-action pair from history records to get maximum action revenue. Other agents adopt their own optimal strategies in the same way, so each agent's target to maximize theirexpected discounted reward and the goal of the whole Multi-Agent system are accordant in this cooperative reinforcement learning approach [7].

Inference rule for agent's current action strategy $\pi^i$ is given as following formula:

$$\pi_{t+1}^i(s) = \begin{cases} \pi_t^i(s) & \text{if } s_t \neq s \text{ or} \max_{a_i \in A_i} q_{t+1}^i(s, a^i) \\ a_t^i & \text{else} \end{cases}$$

From the above we can see, agent will modify its action strategy only when the q-value can be improved, otherwise the original action strategy will be remained. Assuming that each agent adopts such a strategy inference rule, then we can get the joint action strategy: $\pi^u(s) = (\pi^1(s),\ldots,\pi^t(s),\ldots,\pi^n(s))$. With incomplete observation information, agents take action according to state-action pairs of current q value table firstly, and then modify their q value and state-action pair according to the observation of environmental feedback reward. Before agents meet the Nash equilibrium point, they will always be able to find themselves action strategy with higher environmental reward. The global optimal strategy for joint action is reached until each agent can no longer search for better strategy.

## III. Cooperative Control of Strawberry Greenhouse Production

### A. Cooperative Control Frame

For researching of cooperative control in agricultural complex system, we had set the control system in greenhouse for different breeds of strawberry. In the greenhouse, micro climate of three kinds of strawberry A, B, C should be respectively controlled to meet different growth requirements, such as control goals for temperature, light, soil fertilizer nutrient and irrigation. Obviously this greenhouse control system is a complex system which needs cooperative control. Figure 2 is the control frame of the complex system. Based on above cooperative control analysis, we had designed four control agents, lighting control agent A1, soil fertilizer nutrient control agent A2, soil temperature control agent A3, irrigation control agent A4. These agents are used to respectively control a specific kind of environmental variables for three strawberry breeds, and then we got the optimal joint solution for multiple environmental factors through the global optimization of coordinated controller. Specific algorithms are described as follows:

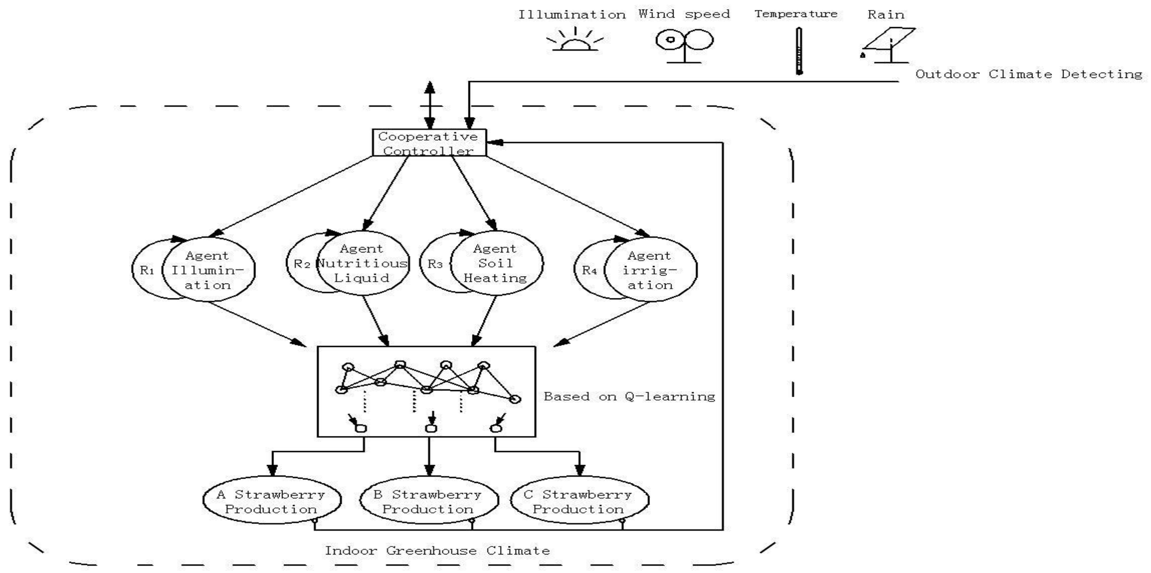


Fig. 2. Control structure for strawberry greenhouse production.

1) Initialize the value function of each agent. The state-action pairs of agent $A1$ is $q^1(s^1(A^1,B^1,C^1),a^1(A^1,B^1,C^1))$, agent $A2$ $q^2(s^2(A^2,B^2,C^2),a^2(A^2,B^2,C^2))$, agent $A3$ $q^3(s^3(A^3,B^3,C^3),a^3(A^3,B^3,C^3))$, agent $A4$ $q^4(s^4(A^4,B^4,C^4),a^4(A^4,B^4,C^4))$. Here $s^i$ represents state of environmental variable; $a^i$ represents the agent's action aggregate responding to environment change. According to strawberry's planting experiment, the three breeds of strawberries have the same action rules as shown in table 1.

TABLE I: CONTROL ACTION RULES OF STRAWBERRIES IN GREENHOUSE

| | Agent A1 | Agent A2 | Agent A3 | Agent A4 |
|---|---|---|---|---|
| 0 | Ordinary light | No need | No heating | No irrigation |
| 1 | Medium light | Differential concentration ratio | Medium temperature | Medium irrigation |
| 2 | High light | Equal concentration ratio | High temperature | High irrigation |

2) Learn from the initial state. Calculate the q values of all possible actions of each agent under state s and choose action $a^{i*}(A^i, B^i, C^i)$ which has the largest q value. Implement action $a^{i*}(A^i, B^i, C^i)$ and observe the next state s' and the reward. Then substitute them into the formula

$$q_{t+1}(s_t, a_t^i) = \max\{q_t^i(s_t, a_t^i), r(s_t, a_t^u) + \gamma \max q_t(s', a^{i'})\}$$

3) Coordinating controller keeps modifying the $q^i$ value and state-action pair according to environmental feedback reward until each control agent has maximized their revenue, then we will get the joint action strategy $\pi^u$. The description matrix of the greenhouse system is as follows:

$$\left\{\begin{matrix} A_{1A} & A_{1B} & A_{1C} \\ A_{2A} & A_{2B} & A_{2C} \\ A_{3A} & A_{3B} & A_{3C} \\ A_{4A} & A_{4B} & A_{4C} \end{matrix}\right\}$$

Here, respectively each line corresponds to the different control agents $A1$, $A2$, $A3$, $A4$, and each column corresponds to the strawberry breeds A, B, C.

After the completion of corresponding control algorithm, each strawberry adaptive control subsystem receives its own agent action $[A_{1A}, A_{2A}, A_{3A}, A_{4A}]$, $[A_{1B} \cdot A_{2B} \cdot A_{3B} \cdot A_{4B}]$, $[A_{1C} \cdot A_{2C} \cdot A_{3C} \cdot A_{4C}]$. Through control actions of the sunshade net, soil heating device, the nutrient solution proportioning and releasing device, irrigation device and so on, we had achieved automatic control of various environmental variables and created the best micro-climate for strawberry growth.

### A. Constraints Design of Strawberry Cooperative Controller

To infer out the optimization results of greenhouse environment control system, we also need to take into account the constraints conditions as a compromise. Accuracy requirements of greenhouse environment control are not as high as industrial control and its values of environmental variables given by cultivation experts are often interval values [8].Under circumstances that environment variables are maintained within the required interval ranges, we can still choose from different control actions to minimize greenhouse system energy consumption. System's environment variables will interact with each other, for example, light exposure will lead to temperature rise, the lack of moisture will cause soil compaction and affect the root absorption of nutrients, high temperature will lead to increased transpiration and decreased humidity, and so on. According to greenhouse cultivation experience, main reasoning expressions of constraints table had been given as below:

"If strawberry lacks both water and fertilizer, then increase irrigation first".

"If the greenhouse is in high temperature and low humidity, then irrigate and stop heating at the same time".

"If the greenhouse lacks lighting and strawberry leaves turn yellow, then increase both illumination and fertilizer".

"If the greenhouse lacks lighting and strawberry suffers from low soil temperature, then increase illumination first".

## IV. CONCLUSION

In this paper, we explored the frame and mechanism of cooperative control and gave constraints conditions and general reasoning expressions in the example of greenhouse strawberry production control system. IA systems in the future will witness more applications of various cooperative controllers. Current researches mainly focus on large-scale coordination and network communications. Future research should emphasize on the adoption of Agent technology to achieve coordinator evolution and intelligent control effects. Research on agricultural subsystems cooperative control has propelled IA research to upgrade new step forward[9][10], but meanwhile there are many noteworthy places that need further attention, such as definition and modeling of cooperative control in an open agricultural environment, constraints inference imposed by agricultural resources and energy consumption.

## ACKNOWLEDGEMENTS

The research work has been supported by National Nature Fund 2011 project name: Optimal Control in Greenhouse System（61174088）.

## REFERENCES

[1] Y. Chen, "Intelligent Agriculture (IA): Looking Forward to Progress of China Agriculture Science and Technology in 12th Five-year Plan Period," *Journal of Agricultural Science and Technology*. 2010, vol. 12, no. 6, pp. 1-4.

[2] J. Liu, Z.-Q. Chen, and Z.-X. Liu, "Advances in Multi-agent Systems and Cooperative Control," *CAAI Transactions on Intelligent Systems*, 2010. 01. 001

[3] P. Stone and M. Veloso, "Multiagent Systems: A survey from a Machine Learning Perspective," *Autonomous Robots*. 2000, vol. 8, pp. 345-383

[4] R. S. Sutton and A. Barto, "Reinforcement Learning: An Introduction." MIT Press, Cambridge, MA, 1998.

[5] X.-M. Li, Y.-P. Yang, and X.-M. Xu, "Research on Multi-agent Cooperation with Markov Game and Reinforcement Learning," *Journal of Shanghai Jiaotong University*, 2001, vol. 35, no. 2, pp. 288-293

[6] M. Lauer and M. Riedmiller, "An algorithm for distributed reinforcement learning in cooperative multi-agent systems," in *proceedings of the Seventeenth International Conference on Machine Learning*, Stanford, CA, 2000. Pp. 535-542

[7] X. Li, Y.-P. Yang, and X.-M. Xu, "Multiagent Cooperative Decision-making based on Independent Learning," *Control and Decision*. 2002, vol. 17, no. 1, pp. 29-33

[8] L. Xu, J. Wu, Q. Wu, and J. Chen, "Coordination algorithm of multiple greenhouse environment variables," China, CN101002533A, 2007-07-25

[9] R. E. King, N. Sigrimis, "Computational Intelligence in Crop Production," *Comp. Electron. Agric*. 2001, vol. 31, no. 1, pp. 1-3

[10] I. Farkas, "Artificial Intelligence in Agriculture," *Comp. Electron. Agric.*, vol. 40, no. 1-3, pp. 1-3, 2003.