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Multi-task Collaboration Cyber-physical System Modeling Based on Immune Feedback

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Abstract

In this paper, a dynamic multi-task collaboration CPS control model based on the self-adaptive immune feedback is proposed and implemented in the smart home environment. First, the internal relations between CPS and the biological immune system are explored via their basic theories. Second, CPS control mechanism is elaborated through the analysis of CPS control structure. Finally, a comprehensive strategy for support is introduced into multi-task collaboration to improve the dynamic cognitive ability. At the same time, the performance of parameters is correspondingly increased by the operator of the antibody concentration and the selective pressure. Furthermore, the model has been put into service in the smart home laboratory. The experimental results show that this model can integrate user's needs into the environment for properly regulating the home environment.

***Keywords**: information-material-energy, cyber-physical systems, control algorithm, dynamic collaboration, immune feedback*

1. Introduction

Cyber-physical System (CPS) is a multi-dimensional heterogeneous network system composed by synthesis computation, network convergence and physical environment. The new functions, such as reliability, high-efficiency, real-time cooperative interaction et al, are dramatically enhanced and extended by feedback loop between virtual processes and physical processes to implement the organic integration and deep collaboration [1-3]. In dynamic CPS, the questions about the uncertainty of interactive objects, the randomness of the interactive environment, platform constraints, the ability of dynamic adjustment and context awareness, and the adaptivity of dynamic service are worthy to pay close attention [4, 5]. For this reason, this paper proposes a multi-task collaboration CPS control model based on immune feedback. And this method combined immune feedback in the biological system with machine learning for implementing the context awareness capacity in the interaction, thus improving the dynamic adjustment ability and solving the uncertainty problem in the CPS.

2. The Relationship between CPS and Biological Immune Feedback System

Immune feedback system is indispensable for biological defense mechanism, especially for vertebrate and human. There are many well-developed antibodies, which can deal with the complex dynamic environment, in biological system. Immune feedback system adopted distributed task processing method could take intelligent behavior on the local scale, and also could build up global control concept in the chemical information network.

The same as biological system, CPS as a large-scale complex system has formed a physical form of joint movement between material and information under the support of energy. In the system, various environment information correlates with material information in cyber layer to establish a network. In order to promote the effective operation of CPS, information provides feedback loops via transmitting in communication medium, circulating, reading and recognizing information. Under the comprehensive connection to information, positive linkage is generated between tings and things for boosting harmonious development in the network system. In CPS, the energy is spent on establishing the internet of things, and the material flow and the information flow are perceived as well as the energy flow [7]. As is shown in Figure 1,

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CPS operation mode is represented by the relations between and among information, material and energy.

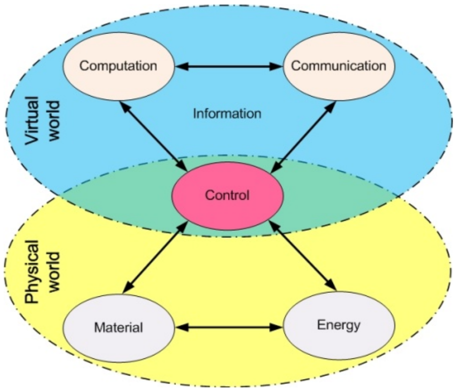

Figure1. CPS Operation Mode

Above elucidates the relation between biological immune feedback system and CPS operation in the abstract level of information-material-energy. Furthermore, CPS adopts distributed control in general, and the scheduling and decision of system depends on central feedback control based on notes' autonomous perception control [8-9]. CPS gives each note the autonomy and optimizes the control precision to increase response speed of system and efficiency of task execution. Then information feedbacks synchronize with actuators.

3. CPS Control Mechanism Based on Multi-task Collaboration

As is shown in Figure 2, monitors collect external environment variables via sensor devices, and in the meantime devices in environment layer and service applications are effectively controlled by the mechanism of local registry. Environment change causes control deviation, and control deviation passes to CPS controller. Then system passes information to auxiliary feedback regulator. In the meantime, monitors get new service by monitoring service registers, and information is transmitted to feedback inhibition regulator. Inhibition quantity TS is used for controlling auxiliary quantity TH, and they are feed back to CPS controller together for eliminating control deviation. When control deviation is larger, the effect of TH is greater than TS. With the decrease of control deviation, the effect of TS increases gradually, and TS restrains the effect of TH. After a period of time, immune feedback system becomes balanced and CPS achieves a relatively stable state.

According to the mechanism of immune feedback regulation, the k generation control deviation is defined as $e(k)$, the output of auxiliary feedback is $T_H(k)$, feedback inhibition to the controller is $T_S(k)$, and the input of controller is $u(k)$. From this feedback control rules are as follows [10].

$$\begin{aligned} u(k) &= T_H(k) - T_S(k) \\ &= k_1 e(k) - k_2 f[\Delta u(k)]e(k) \\ &= K\{1 - \eta f[\Delta u(k)]\}e(k) \end{aligned} \tag{1}$$

Where $K = k_1$, $\eta = k_2 / k_1$, and $f[\bullet]$ is a nonlinear function. In formula (1), parameter K controls response speed, η regulates system's stability. $u(k) = K_p e(k)$ is control algorithm of normal P controller, and K_p is proportional gain. Therefore, the controller based on immune feedback is a nonlinear P controller, and its proportional gain is $\overline{K}_p = K\{1-\eta f[\Delta u(k)]\}$. The properties of controller are correlated with K, η and $f[\bullet]$ [11].

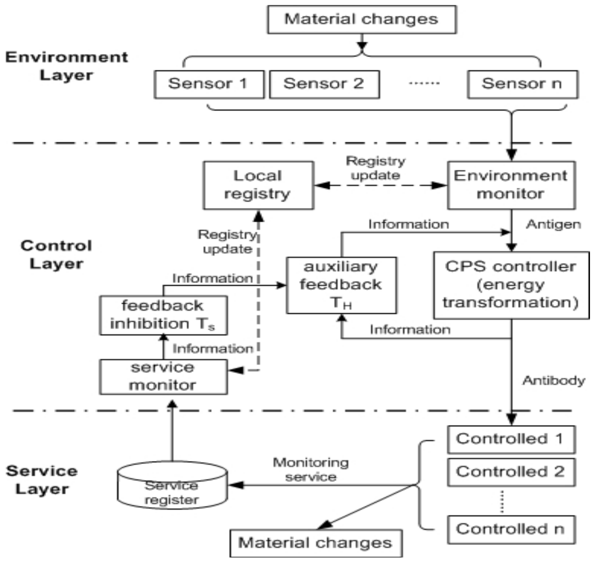

Figure 2. CPS Control Mechanism Based on Immune Feedback

4. Analysis of CPS Model
4.1. Dynamic Multi-task Collaboration Model of CPS

CPS is basis of layered structure and heterogeneous network environment, so the function is relatively independent and collaborative form is more flexible among subsystems. But under the above advantages, there are still some challenges about decision and collaboration among subsystems. For this reason, this paper uses Fuzzy Cognitive Map (FCM) to build system support model. And on this basis comprehensive collaboration and decision strategies are proposed to realize the coordination control in decentralization subsystems.

4.1.1. Expression of Fuzzy Cognitive Map in CPS

As is shown in Figure 3, relatively independent function part in sensing and service layer of CPS could be defined as a subsystem a_i. s_i is the support to task or decision t from subsystem a_i, and weight w_{ij} calculated by reference [12] is the correlation between notes i and j. Then support s_i is quantitatively described by NPN fuzzy logic in $[-1,1]$.

In this CPS intelligent control system, correlation is weak among the subsystems, namely the support of any subsystem a_i to task or decision t only influences a part of other subsystems. In this paper, $w_{ij} \in [-1,1]$. When $w_{ij} > 0$, subsystem i is play an positive role in j. When $w_{ij} < 0$, subsystem i enhances the function of inhibition in j. When $w_{ij} = 0$, subsystem i and subsystem j are not related to each other. So the system's incidence matrix is:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix}$$

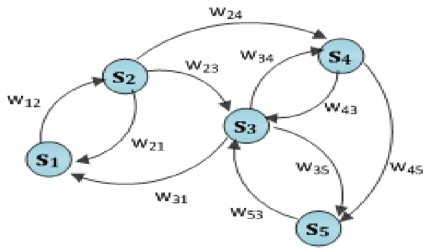

Figure 3. Fuzzy Cognitive Map expression of CPS

4.1.2. Weight Value of Subsystem

As is shown in Figure 3, there are direct and indirect relation paths among subsystems. Own associated link is introduced and its weight value $w_{ii}=1$, so $i \to j$ equivalents for $i \to < e_1, e_2 > \to j$. Here, $e_1 =< i, i >$, $e_2 =< i, j >$. Associated weight value between a_i and a_j is $w_{ii}'|_{<e_1,e_2>} = w_{ii}w_{ij} = w_{ij}$. In this case, the direct relation can be converted to indirect.

Subsystem a_i is associated with $a_j\ (i \neq j)$ via m paths in FCM, and weight value is $w_{ij}'^{(1)}, w_{ij}'^{(2)}, \cdots w_{ij}'^{(m)}$ respectively. $r_{ij} = (\min\{0, w_{ij}'^{(k)}\}, \max\{0, w_{ij}'^{(k)}\}), k=1,\cdots m$ is calculated through integrated computation of m associated weights. Here, $r_{ij}^{-} = \min\{0, w_{ij}'^{(k)} \mid k=1,\cdots m\}$ and $r_{ij}^{+} = \max\{0, w_{ij}'^{(k)} \mid k=1,\cdots m\}$.

In $R^q = [r_{ij}^{(q)}]_{n\times n}$, $r_{ik}^{(q)}$ is the maximum negative and positive associated weight from note i to k in the path which length is q, namely $r_{ik}^{(q)} = (r_{ij}^{(q)-}, r_{ij}^{(q)+})$.

4.1.3. Comprehensive Strategy for Support in Subsystems

Because CPS has good distribution and expansion properties, support interval coordination method is used for system decision. The system depends on the maximum intensity of support and objection and ignores the neutral constructive attitude to reduce computational complexity. Specific support strategy is as follows.

(1) Initial support vector of subsystem is converted to support degree:

$$[(s_1^-(0), s_1^+(0)), (s_2^-(0), s_2^+(0)), \cdots, (s_n^-(0), s_n^+(0))] = [(\min\{0, s_1(0)\}, \max\{0, s_1(0)\}), \cdots, (\min\{0, s_n(0)\}, \max\{0, s_n(0)\})]$$

(2) Correlative support degree matrix of subsystem is:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1i} \cdots r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2i} \cdots r_{2n} \\ \vdots & \vdots & \ddots & \vdots \ddots \vdots \\ r_{n1} & r_{n2} & \cdots & r_{ni} \cdots r_{nn} \end{bmatrix}$$

(3) Support degree of subsystem is calculated by R.

$$\begin{bmatrix} s_1^-(k+1), s_1^+(k+1) \\ s_2^-(k+1), s_2^+(k+1) \\ \vdots \\ s_n^-(k+1), s_n^+(k+1) \end{bmatrix}^T = \left((s_1^-(k), s_1^+(k)) \quad \cdots \quad (s_n^-(k), s_n^+(k))\right) \bullet R$$

(4) Comprehensive support degree is:

$$S = \begin{bmatrix} s_1^-(2n-1)+s_1^+(2n-1) \\ s_2^-(2n-1)+s_2^+(2n-1) \\ \vdots \\ s_n^-(2n-1)+s_n^+(2n-1) \end{bmatrix}^T$$

4.2. Intelligent Control Algorithm of CPS Based on Self-adaptive Immune Feedback

When control deviation first appears, feedback control method does not exist in the system. So the system adapts to traditional control algorithm, such as PID, to eliminate the control deviation, and learns to produce feedback control quantity next. When this control deviation appears again, the feedback control comes into effect. In this process, the original control quantity not necessarily matches new control deviation, so system first seek out the best fit feedback quantity from the memory and we translate this quantity into a more appropriate one by self-adaptive mutation. Then the more appropriate feedback quantity will be added to memory. Based on biological immune feedback regulation, this algorithm introduces a self-adaptive variation method to withstand the disturbance from complex and volatile environment. Compared with traditional control system, this CPS improves its adaptability through control deviation recognition, a variety of feedback adjustment, self-adaptive variation and memory updates.

Control algorithm flow based self-adaptive immune feedback in CPS is as Figure 4.

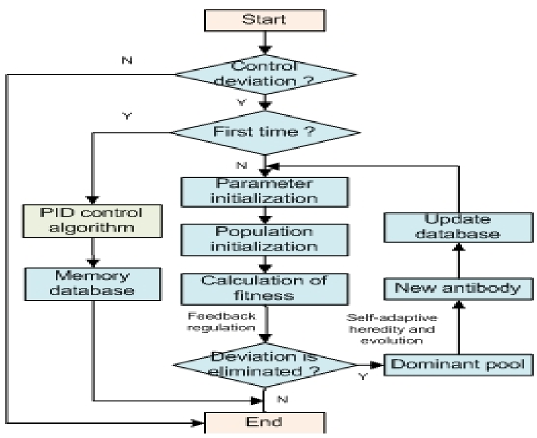

Figure 4. Algorithm Flow Chart

4.2.1. Control Deviation Recognition

Control deviation is used to judge whether external disturbance occurs. Control deviation $e(k)$ is greater than the set thresholds, namely the deviation appears. CPS improves its operation speed and control performance through timely deviation recognition.

4.2.2. Population initialization

(1) The generation of initial population. If the disturbance ever happened, initial population is selected from the memory vault. Otherwise, the initial population is randomly generated. On the basis of Simple Genetic Algorithm, selection pressure factor joins in the fitness-proportionate selection to keep the population diversity early on, reduce searching area in later period, and improve the speed of seeking optimal solution. Concentration adjustment factor is introduced to implement ego adjustment function. Selective probability of feedback quantity is shown in formula (2).

$$\begin{aligned} p_i &= \alpha p_{fi} + (1-\alpha)p_{di} \\ &= \alpha \frac{F_i}{\sum_{i=1}^{N} F_i} + (1-\alpha)\frac{1}{N}\cdot e^{-\frac{C_i}{\beta}} \end{aligned} \qquad (2)$$

Where α and β are regulation constant, N is the total number of antibodies, C_i is the concentration of antibodies, and F_i is the fitness function of antibodies $i=1,2,\cdots,N$.

Encoding. Gray code has looping and single-step features, and can effectively reduce the probability of significant errors in random access process. In addition, Gray code is easy to reflect the structure characteristics of problem, and is beneficial to improve random characteristics and local searching ability in genetic operation. So this paper uses Gray code to encode individual in the population.

4.2.3. Self-adaptive Heredity and Evolution of Feedback Quantity

(1) Crossover and variation. First, there are three stages in crossover, $[0,0.382Mgen]$, $[0.382Mgen,0.618Mgen]$ and $[0.618Mgen,Mgen]$. Here, $Mgen$ is the maximal evolution generations. The calculation formula of crossover probability is:

$$p_c=\begin{cases}\frac{p_{c1}+p_{c2}}{2}+\frac{p_{c1}-p_{c2}}{2}\times\sin\frac{(F_i-F_{avg})}{F_{\max}-F_{avg}} & F_i\ge F_{avg}\\ \frac{p_{c1}+p_{c2}}{2} & F_i<F_{avg}\end{cases} \quad (3)$$

And the calculation formula of variation probability is:

$$p_m=\begin{cases}\frac{p_{m1}+p_{m2}}{2}+\frac{p_{m1}-p_{m2}}{2}\times\sin\frac{(F_i-F_{avg})}{F_{\max}-F_{avg}} & F_i\ge F_{avg}\\ \frac{p_{m1}+p_{m2}}{2} & F_i<F_{avg}\end{cases} \quad (4)$$

Where p_{c1}, p_{c2}, p_{m1}, p_{m2} is the upper and lower limit of crossover probability, variation probability respectively, F_i is the fitness of individual x_i, F_{avg} is population's average fitness, $F_{\max}$ is the maximal fitness.

(2) Fitness function.

$$F_i=\frac{\exp\left(F(x_i)/T\right)}{\sum_{i=1}^{N}\exp\left(F(x_i)/T\right)} \quad (5)$$

$$F_{avg}=\frac{\sum_{i=1}^{N}F_i}{N} \quad (6)$$

Where, pressure factor $T=T_0\times 0.99^{gen}$; gen is current genetic generation; $i=1,2,\cdots,N$, N is the population size; $F(x_i)$ is the objective function of individual x_i; F_i is x_i's fitness; and F_{avg} is x_i's average fitness.

(3) Objective function.

$$F(x_i)=\gamma\|sp(x)-sp_i(x_0)\|+(1-\gamma)\|e(x)-e_i(x_0)\| \quad (7)$$

Where $sp(x)$, $e(x)$ is eigenvalue of control deviation; $sp_i(x_0)$, $e_i(x_0)$ is antibodies' eigenvalue and $0<\gamma<1$.

4.2.4. Memory Database Update

The antibody which has higher fitness is added to memory database. In order to limit size, new feedback quantity is added to memory database, and all the feedback quantities are descending sorted based on affinity. Then the antibody which has lower fitness is eliminated for maintaining the accuracy and diversity of feedbacks.

4.2.5. Controllers' Feedback Regulation

According to CPS control mechanism based on immune feedback mentioned in section 2, system produces a corresponding inhibition and auxiliary effect.

5. Experiments

We put above model into smart home, a miniature CPS, for proving its validity. The smart home in our experiment is a studio apartment. There are a gateway, an air condition, a television, a refrigerator, a washing machine, six electric lamps, five outlets, four cameras, an electric meter, and multiple environmental sensors, such as temperature sensor, humidity sensor etc, which are intelligent and controllable, and some living facilities. Overall distribution of the smart home is shown in Figure 5.

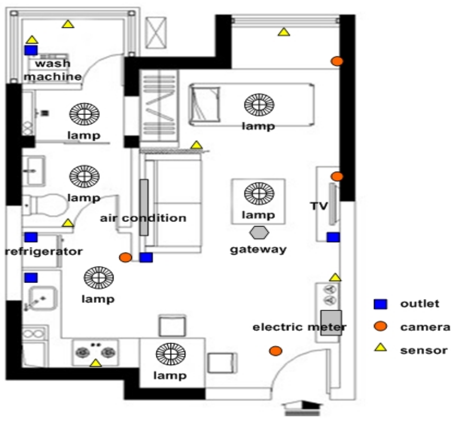

Figure 5. Overall Distribution of the Smart Home

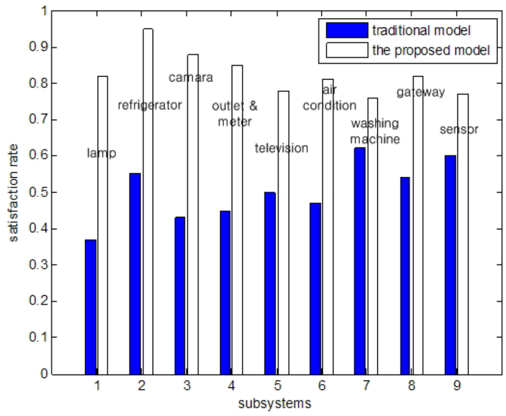

Figure 6. Accuracy and reasonable rate of multi-task collaboration in the smart home

Traditional statical multi-task collaboration model based on simple genetic algorithm and the CPS model in this paper are applied to the smart home respectively as a comparison task. First, 30 participants take notes on outputs of each equipment in different temperature, humidity, and requirement. The experimental results (in Figure 6) show that compared with traditional algorithm, multi-task collaboration model based on immune feedback makes control more reasonable and accuracy among each subsystems.

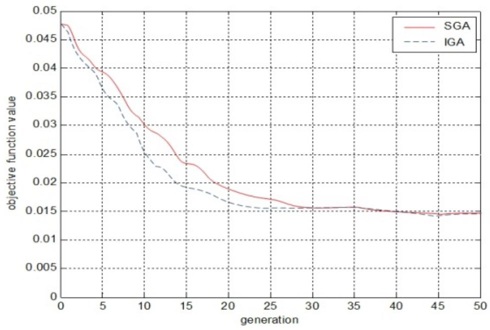

Figure 7. Convergence of Objective Function

Figure 7 is simulation curves about simple genetic algorithm and self-adaptive immune genetic algorithm. Convergence generation of self-adaptive immune genetic algorithm mentioned in this paper is about 20, but simple genetic algorithm is about 25. And their convergence value of objective function is both 0.015. It means that in the case of same accuracy, convergence rate of self-adaptive immune genetic algorithm is superior to simple genetic algorithm. It is chiefly because antibodies' concentration factor C_i is introduced to selection probability for increasing the capability of immune feedback regulation, pressure factor T gives less selection pressure in early population evolution to keep population's diversification and gives great selection pressure in later to reduce the searching area and speed up the improvement of optimal solution.

6. Conclusion

For the complexity and adaptivity, this paper improves the model of biological immune system, and it is used to analyze the relationship of information-material-energy in CPS. And on this basis this paper proposes a multi-task collaboration CPS control algorithm based on biological immune feedback mechanism, and the comprehensive strategy for support is introduced to multi-task collaboration to sharply increase dynamic cognitive capability. Meanwhile concentration of antibodies and selective pressure factor are applied to CPS optimization, and improve the parameters' performance. On the basis of this model, all the subsystems can realize more accurate self-adaptive regulation in smart home. Thereby this system can achieve an intelligent and humanized home control with environmental changes. This model uses in smart home where 30 participants live in turn. Experimental results shows that this system can give full play to equipments' initiative and adaptability in smart home, and throws off the mechanized control method in traditional home.

References

[1] LIU Zhong, YANG Dong-sheng, et al. Cyber-Physical-Social Systems for Command and Control. *Cyber-Physical-Social Systems.* 2011; 92-96.

[2] ZHAO Jun-hua, WEN Fu-shuan, et al. Modeling analysis and control research framework of cyber physical power systems. *Automation of Electric Power Systems*. 2011; 35(16): 1-8.

[3] LIU Xiang-zhi, LIU Xiao-jian, et al. A cyber- physical system. *Shangdong Science*. 2010; 23(3): 1-8.

[4] Mardiyono, Suryanita Reni, et al. Intelligent monitoring system on prediction of building damage index using neural-network. *Telkomnika*. 2012; 10(1): 155-164.

[5] Wang Zhong-jie, Xie Lu-lu. Cyber-physical systems: A surey. *Acta Automatica Sinica*. 2011; 37(10): 1157-1166.

[6] Kebai Li, Yuhua Zhao. Robust control of urban industrial water mismatching uncertain systme. *TELKOMNIKA Indonesian Journal of Electrical Engineering.* 2013; 11(1): 494-502.

[7] Zhu Yonghong, Feng Qing, et al. Neural network-based asaptive passive output feedback control for MIMO uncertain system. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(6): 1263-1272.

[8] Abdelzaher T. Research challenges in distributed cyber-physical system. IEEE/IFIP International Conference on Embedded and Ubiquitous Computing. Shanghai. 2008; 5-10.

[9] Mikael Lindberg, Karl-Erik Årzén. Feedback control of cyber-physical systems with multi resource dependencies and model uncertainties. 31st IEEE Real-Time Systems Symposium. California. 2010; 85-94.

[10] Takahashi K, Yamada T. Application of an immune feedback mechanism to control systems. *JSME International Journal, Series C*, 1998; 41(2): 184-191.

[11] Ding Yong-sheng, Tang Ming-hao. An intelligent control system with limunity feedback. *Process Automation Instrumentation.* 2001; 22(10): 5-7.

[12] Chrysostomos D Stylios, P Groumpos. The challenge of using soft computing methodologies in supervisory control systems. IFAC 14th Triennial World Congress. Beijing. 1999; 285-290.

[13] Zhang Wenran, Chen Sushing. Pool2: A generic system for cognitive map development and decision analysis. *IEEE Transactions on system, man and cybernetics.* 1989; 19(1): 31-39.

[14] Miao Yuan, Miao Chunyan, et al. Transformation of Cognitive Maps. *IEEE Transcations on fuzzy system.* 2010; 18(1): 114-124.