Intelligent AVR Control Using Hybrid Optimization Based On Bacterial Foragiung and Clonal Selection

Dong Hwa Kim[1], Jae Hoon Cho[2]
[1]Dept. of Instrumentation and Control Eng., Hanbat National University,
16-1 San Duckmyong-Dong Yuseong-Gu, Daejon City, Korea, 305-719.
E-mail: kimdh@hanbat.ac.kr, Hompage: aialab.net
[2] School of Electrical and Electronic Engineering, Chungbuk National University,
12 Gaesin-Dong, Cheong-Ju, Chungbuk, Korea. 361-763

Abstract: *This paper suggests novel hybrid optimization system (BF-CL) based on the bacterial foraging and clonal selection of immune system. A foraging strategy involves finding a patch of optimal condition (e.g., group of objective with conditions), deciding whether to enter it and search for optimal conditions, and when to leave the patch. There are predators and risks, energy required for optimization, and physiological constraints (sensing, memory, cognitive capabilities). Foraging scenarios can be modeled and optimal policies can be found using, for instance, dynamic programming. This approach provides us with novel hybrid model based on foraging behavior and clonal selection for a higher running time and with also a possible new connection between evolutionary forces in social foraging and distributed nongradient optimization algorithm design for global optimization over noisy surfaces for control system.*

Keywords: PID control, Clonal Selection, Bacteria survival strategy, Hybrid system

1. Introduction

The Proportional–Integral–Derivative (PID) controller has been using in the most control loops of plant despite continual advances in control theory such as process control, motor drives, thermal power plant and nuclear power plant, automotive, fight control, instrumentation. This is why the advantage of a PID controller includes simplicity, robustness but it cannot effectively control such a complicated or fast running system. However, this control approach has some problems with tuning such as oscillatory operation’s problems, difficulty of physical characteristics in real system. That is, since most of the PID tuning rules developed in the past years use the conventional method such as frequency-response methods, this method needs a highly technical experience to apply as well as they can not provide simple tuning approach to determine the PID controller parameters. For example, the Ziegler-Nichols approach often leads to a rather oscillatory response to set-point changes because the system has non-linearities such as directionally dependent actuator and plant dynamics, and various uncertainties, such as modeling error and external disturbances, are involved in the system [1-2]. Due to a result of these difficulties, the PID controllers in multivariable process are rarely tuned optimally. Therefore, to improve the performance of PID tuning for processes with changing dynamic properties, the complicated system, and dead time process, several tuning strategies such as, automatic tuning PID, intelligent tuning technique, and decoupling approaches have been proposed.

On the other hand, in the last decade, evolutionary computation based approaches have received increased attention from the engineers dealing with problems which could not be solved using conventional problem solving techniques [4-5]. The general problem of evolutionary algorithm based engineering system design has been tackled in various ways. GA has also been used to optimize nonlinear system strategies. Among them, a large amount of research is focused on the design of fuzzy controllers using evolutionary algorithm approaches. On the other hand, as natural selection tends to eliminate animals with poor foraging strategies through methods for locating, handling, and ingesting food and favor the propagation of genes of those animals that have successful foraging strategies, they are more likely to apply reproductive success to have an optimal solution [4], [5]. Since a foraging animal takes actions to maximize the energy obtained per unit time spent foraging, in the face of constraints presented by its own physiology such as, sensing and cognitive capabilities and environment (e.g., density of prey, risks from predators. physical characteristics of the search area), evolution can provide optimization within these constraints and essentially apply to engineering field by what is sometimes referring to as an optimal foraging policy. That is, optimization models can provide for social foraging where groups of parameters communicate to cooperatively forage in engineering. First, this paper provides a brief literature overview of the area of bacterial foraging as it forms the biological foundation for this paper. Then, this paper also focuses on dealing with an enhanced optimal solution using a hybrid approach consisting of BA (Bacterial Foraging) and CL (Clonal Selection). Finally, we focus on evidence for the proposed hybrid system for control system.

However, the PID controller parameters of multivariable system are still computed using the classic tuning formulae and these can not provide good control performance in control situations. When there is the disturbance in a PID controller loop, the design of a PID controller has to take care of specifications on responses to the disturbance signals as well as robustness with respect to changes in the process [4]. Since load disturbances between loops in multivariable process are often the most common problems in process control, most design methods should therefore focus on disturbance rejection due to decoupling approach and try to find a suitable compromise between demands on performance at load disturbances and robustness [5].

2. HYBRID OPTIMIZATION BASED ON BACTERIA FORAGING AND CLONAL SELECTION FOR CONTROL SYSTEM

Mutations in E. coli affect the reproductive efficiency at different temperatures, and occur at a rate of about 10^{-7} per gene and per generation. E. coli occasionally engages in a conjugation that affects the characteristics of a population of bacteria. Since there are many types of taxes that affect bacteria, such as: aerotaxis attracting to oxygen, phototaxis by light, thermotaxis by temperature, magnetotaxis, bacteria can be affected by magnetic lines of flux and some bacteria can change their shape and number of flagella which is based on the medium to reconfigure in order to ensure efficient foraging in a variety of media. Bacteria can form intricate stable spatio-temporal patterns in certain semisolid nutrient substances and they can eat radially their way through a medium if placed together initially at its center. Moreover, under certain conditions, they will secrete cell-to-cell attractant signals so that they will group and protect each other.

The main goal of applying the Hybrid GA-CL system based on bacterial foraging is to find the minimum of $P(\phi),\ \phi \in R^n$, not in the gradient $\nabla P(\phi)$. Here, ϕ is the position of a bacterium, and $J(\phi)$ is the attractant-repellant profile. That is, it means where the nutrients and noxious substances are located, so the values *P<0*, *P=0, P>0* represent the presence of nutrients. A neutral medium, and the presence of noxious substances, respectively can be defined by [13],

$$H(j,k,l) = \{\phi^i(j,k,l) \mid i = 1,2,...,N\}.$$

Equation represents the positions of each member in the population of the *N* bacteria at the *j*th chemotactic step, *k*th reproduction step, and *l*th elimination-dispersal event. Let *P*(*i*, *j*, *k*, *l*) denote the cost at the location of the *i*th bacterium $\phi^i(j,k,l) \in R^n$, and

$$\phi^i = (j+1,k,l) = \phi^i(j,k,l) + C((i)\varphi(j)\ , \tag{1}$$

so that *C*(*i*)>0 is the size of the step taken in the random direction specified by the tumble. If at $\phi^i(j+1,k,l)$ the cost *J*(*i, j+1, k, l*) is better (lower) than at $\phi^i(j,k,l)$, then another chemotactic step of size *C*(*i*) in this same direction will be taken and repeated up to a maximum number of steps N_s. N_s is the length of the lifetime of the bacteria measured by the number of chemotactic steps. Functions $P_c^i(\phi)$, *i*=1, 2, . . . , *S*, to model the cell-to-cell signaling via an attractant and a repellant is represented by [8-12]

$$P_c(\phi) = \sum_{i=1}^{N} P_{cc}^{i} = \sum_{i=1}^{N} \left[-L_{attract} \exp\left(-\delta_{attract} \sum_{j=1}^{n} (\phi_j - \phi_j^i)^2 \right) \right] + \sum_{i=1}^{N} \left[-K_{repellant} \exp\left(-\delta_{repellant} \sum_{j=1}^{n} (\phi_j - \phi_j^i)^2 \right) \right] \tag{2}$$

where $\phi = [\phi_{1,\ldots,}\phi_p]^T$ is a point on the optimization domain, $L_{attract}$ is the depth of the attractant released by the cell and $\delta_{attract}$ is a measure of the width of the attractant signal. $K_{repellant} = L_{attract}$ is the height of the repellant effect magnitude, and $\delta_{attract}$ is a measure of the width of the repellant.

3. INTELLIGENT CONTROL SYSTEM USING HYBRID SYSTEM BF-CL

3.1 Gain Margin and Phase Margin in Control System

When the PID controller is given as

$$K(s) = k_p \left(1 + \frac{1}{sT_i} + sT_d \right), \tag{3}$$

and the process is given by

$$G_p(s) = \frac{k_c}{1 + s\tau} e^{-sL}, \tag{4}$$

the loop transfer function is obtained by

$$KP_p(s) = \frac{k_p k(1 + sT_i)}{sT_i(1 + s\tau)} e^{-sL}. \tag{5}$$

On the other hand, the basic definitions of phase margin and gain margin are given as [15]:

$$G_m = \frac{1}{\left|K(j\omega_c)G_p(j\omega_p)\right|}, \tag{6}$$

$$\Phi_m = \arg\left[K(j\omega_c)G_p(j\omega_p)\right] \tag{7}$$

Substituting equation (3) into (4)-(5) gives

$$\frac{1}{2}\pi + \arctan\omega_p T_i - \arctan\omega_p\tau - \omega_p L = 0, \tag{8}$$

$$G_m k_p k = \omega_p T_i \sqrt{\frac{\omega_p^2\tau^2 + 1}{\omega_p^2 T_i^2 + 1}}, \tag{9}$$

$$k_p k = \omega_g T_i \sqrt{\frac{\omega_g^2\tau^2 + 1}{\omega_g^2 T_i^2 + 1}}, \tag{10}$$

$$\Phi_m = \frac{1}{2}\pi + \arctan\omega_g T_i - \arctan\omega_g\tau - \omega_g L. \tag{11}$$

For process given as k, τ, L and specifications defined by G_m, Φ_m. Equations (8)-(11) can be solved for the PID controller parameters, k_p, T_i, T_d and crossover frequencies ω_g, ω_p numerically but analytically because of the presence of the arctan function. Through reference [15], final gain margin and phase margin can be given by

$$G_m = \frac{\pi\tau}{4kL}\left(1 + \sqrt{1 - \frac{4L}{\pi T_i} + \frac{4L}{\pi\tau}}\right), \tag{12}$$

$$\Phi_m = \frac{1}{2}\pi - \frac{kk_p L}{\tau} + \frac{\pi}{4k_p k}\left(1 - \frac{\tau}{T_i}\right). \tag{13}$$

Whatever the design approach, tuning technique based on gain margin and phase margin can has robustness and stability without plant operation condition.

The transfer function of PID controller in the control system and requirement condition for controlling safety are given by

$$G_c(s) = K_c\left(1+\frac{1}{sT_i}+sT_d\right) = \frac{K_cT_d}{s}\left(s^2+\frac{1}{T_d}s+\frac{1}{T_iT_d}\right) \tag{14}$$

$$F = \frac{1}{\alpha\{(A_m - A_m^*)^2 + (\phi_m - \phi_m^*)^2\} + \beta(ISE)}$$

and block diagram of the control system is shown in Fig. 1. The performance index of control response is defined by

$$\begin{aligned}\min F(k_p,k_i,k_d) &= \frac{e^{-\beta}\cdot t_s/\max(t)}{\left(1-e^{-\beta}\right)\cdot\left|1-t_r/\max(t)\right|} + e^{-\beta}\cdot Mo + ess \\ &= \frac{e^{-\beta}\cdot\left(t_s+\alpha_2\cdot\left|1-t_r/\max(t)\cdot Mo\right|\right)}{\left(1-e^{-\beta}\right)\cdot\left|1-t_r/\max(t)\right|} + ess \\ &= \frac{e^{-\beta}\cdot\left(t_s/\max(t)+\alpha\cdot Mo\right)}{\alpha} + ess.\end{aligned} \tag{15}$$

$$\alpha = \left(1-e^{-\beta}\right)\cdot\left|1-t_r/\max(t)\right|$$

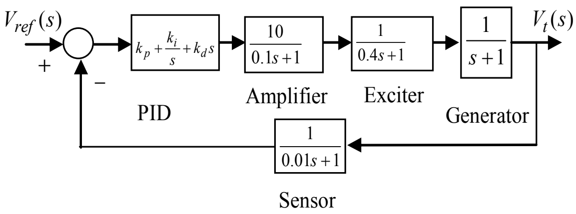

Fig. 1. Block diagram of a control system with a PID controller.

k_p, k_i, k_d : Parameter of PID controller, β : Weighting factor, Mo : Overshoot, t_s : Settling time (2%), ess : Steady-state error, t : Desired settling time. In equation (4), if the weighting factor, β increases, rising time of response curve is small, and when β decreases, rising time is big. Performance criterion is defined as

$Mo = 50.61\%,\ ess = 0.0909,\ t_r = 0.2693(s),\ t_s = 6.9834(s)$.

3.2 BF-CL based Optimization for Control System

This paper describes the method in the form of an algorithm to search optimal value of parameters [11-13].

[step 1] Initialize parameters *n, N, N_C, N_S, N_{re}, N_{ed}, P_{ed}, C(i)(i=1,2,…,N)*, ϕ^i , Where, n: Dimension of the search space, N: The number of bacteria in the population, N_C : chemotactic steps, N_{re} : The number of reproduction steps, N_{ed} : the number of elimination-dispersal events, P_{ed} : elimination-dispersal with probability, C(i): the size of the step taken in the random direction specified by the tumble.

[step 2] Elimination-dispersal loop: $l=l+1$
[step 3] Reproduction loop: $k=k+1$
[step 4] Chemotaxis loop: $j=j+1$.
[step 5] Compute objection function and store best individuals in memory cell of clonal selection loop.
 [substep a] Differentiate clone from memory cell
 [substep b] Compute objective function for clonal bacteria done cross over and store in memory cell by best value order.
[step 6] Decide search direction of bacteria foraging action after objective function in memory cell and objective function of [step 5].

TABLE I.
PARAMETER RANGES FOR LEARNING OF GA-BF.

Parameters	Value
N: The No. of BF group	100
Nc: The No. of chemotaxis loop	300
Nre : The No. of reproduction steps	2
Ned: The number of elimination-dispersal events	5
Ped: elimination-dispersal with probability	0.5
T: The No. of clones	5
Tm: Probability of crossover of clone	0.25
A_m^* : Gain margin of plant	2.5
ϕ_m^* : Phase margin of plant	45

[step 7] If $j < N_C$, go to step 5. In this case, if chemotaxis loop and objective function are satisfied by user, stop calculation, otherwise go to [step 5] computing chemotaxis loop until the life of the bacteria is over.

[step 8] If $k < N_{re}$, go to [step 4]. In this case, we have not reached the number of specified reproduction steps, so we start the next generation in the chemotactic loop.

[step 9] If $l < N_{ed}$, go to [step 3]. In this case elimination-dispersal: For $i = 1,2...,N$, with probability P_{ed}, eliminate and disperse each bacterium, and this results in keeps the number of bacteria in the population constant. To do this, if you eliminate a bacterium, simply disperse one to a random location on the optimization domain.

4. Simulation Results and Discussion

Fig. 2 is showing computation procedure of optimal solution based on BF-CL learning suggested in this paper. Fig. 3 represents computation results of BF-CL and FNN. In this figure, we can see computation method proposed in this paper has more stable step response and lower hunting than FNN. Fig. 4 is speed tracking of indirect vector PI controller(time : 0~0.13 sec). This figure shows more stable response and lower hunting in speed tracking than other control methods. Table I is parameter ranges for Learning of GA-BF and Table II is comparison results of BF-CL and Ref. [4] in control performances.

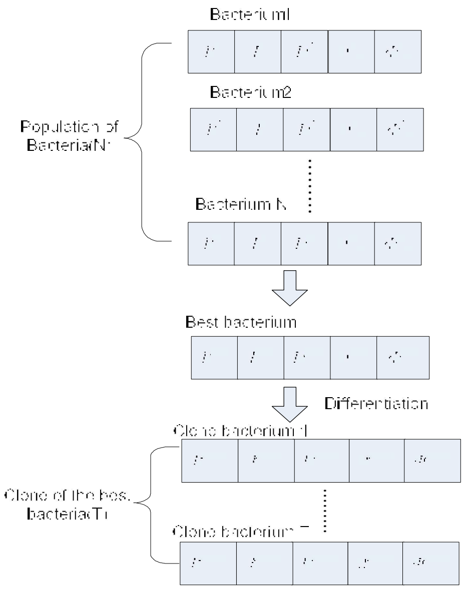

Fig. 2. Computation procedure of optimal solution based on BF-CL learning.

5. CONCLUSION

Recent many approaches of evolutionary of intelligence algorithms for the evaluation of improved learning algorithm and control engineering have been studying. The general problem of evolutionary algorithm based engineering system design has been tackled in various ways because of learning time and local or suboptimal solution.

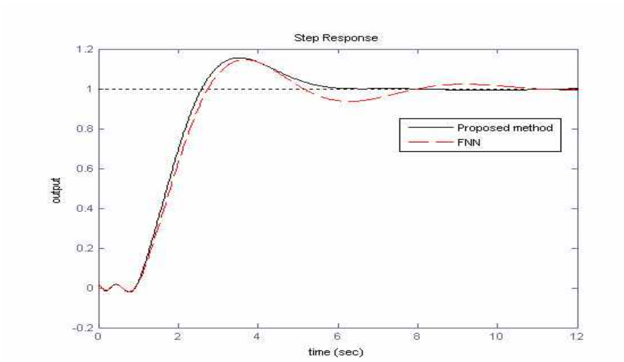

Fig. 3. Computation results of BF-CL and FNN.

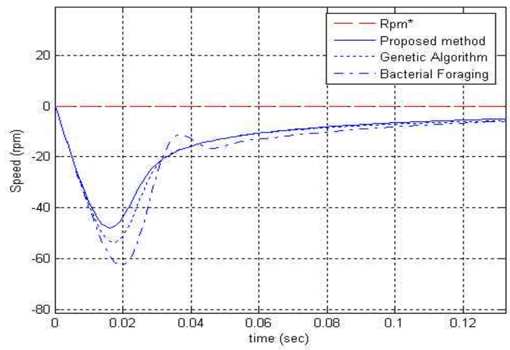

Fig. 4. Speed tracking of indirect vector PI controller (time : 0~0.13 sec).

TABLE II .

COMPARISON RESULTS OF BF-CL AND REF. [4].

Method	P	I	D	A_m	ϕ_m	ISE
Ho[4]	0.68	0.60	0.60	2.3	57	2.223
BF-CS	0.66	0.68	0.71	2.3	52	2.327

TABLE III.

PI PARAMETERS FOR EACH METHOD

Method	Speed control		Current control	
	Kp	Ti	Td	Td
Bacterial Foraging	0.98	0.55	4.54	82.72
Genetic Algorithm	0.93	0.76	6.56	114.21
Proposed Algorithm	0.99	0.64	5.32	85.62

GA has also been used to optimize nonlinear system strategies but it might be local optimized. This paper suggests the hybrid system consisting of BF (Bacterial foraging Algorithm) and CL (Clonal Selection) for PID controller of control system and compared with BF-CL. This approach proposed in this has the potential to be useful in practical optimization problems (e.g., engineering design, online distributed optimization in distributed computing and cooperative control) as models of social foraging are also distributed nongradient optimization methods. It can also may be used a wide variety of fruitful research directions and ways to improve the models (e.g., modeling more dynamics of cell motion).

GA has also been used to optimize nonlinear system strategies but it might be local optimized. Among optimization, a large amount of research is focused on the design of fuzzy controllers using evolutionary algorithm approaches. GA could be used for developing the knowledge based learning about the controlled process in the form of linguistic rules and the fine tuning of fuzzy membership function. However, it may also have problem with local optimization or suboptimal solution.

This section suggests the hybrid system consisting of GA (Genetic Algorithm) and BF (Bacterial Foraging) and proved the characteristic of that system using various test functions.

This approach proposed in this chapter has the potential to be useful in practical optimization problems (e.g., engineering design, online distributed optimization in distributed computing and cooperative control) as models of social foraging are also distributed nongradient optimization methods. It can also may be used a wide variety of fruitful research directions and ways to improve the models (e.g., modeling more dynamics of cell motion).

Moreover, other species of bacteria or biological based computing approach could be studied but it remains to be seen how practically useful the optimization algorithms are for engineering optimization problems, because they depend on the theoretical properties of the algorithm, theoretical and empirical comparisons to other methods, and extensive evaluation on many benchmark problems and real-world problems.

In this paper, we introduce the suggested approach into PID controller tuning of AVR system by BA-CL approach and this method is showing satisfactory results.

References

[1] Dong Hwa Kim, "Genetic Algorithm Combined with Particle Swarm Optimization/Bacterial Foraging and Its Application to PID Controller Tuning," TIT (Tokyo Institute of Technology), Thesis, April, 2006.

[2] Sheng-Yuan Chu and Ching-Cheng Teng, "Tuning of PID controllers based on gain and phase margin specifications using fuzzy neural network, "Fuzzy sets and systems, 101, pp. 21-30, 1999.

[3] Weng Khuen, Chang Chien Hang, and Liseng S. Cao, "Tuning of PID controllers based on gain and phase margin specifications," Automatica, Vol. 31, No. 3, pp. 497-502, 1995.

[4] Chung-Liang Lin, Huai-Wen Su, "Intelligent control theory in guidance and control system design: an Overview," Proc. Natul. Sci., Counc. ROC(A), vol. 24, no. 1, pp. 15-30, 2000.

[5] P. J. Fleming and R. C. Purshouse, "Evolutionary algorithms in control system engineering: A survey," Control Eng. Practice, vol. 10, pp. 1223–1241, 2002.

[6] G. J. Gray, D. J. Murray-Smith, Y. Li, K. C. Sharman, and T. Weinbrenner, "Nonlinear model structure identification using genetic programming," Contr. Eng. Practice, no. 6, pp. 1341–1352, 1998.

[7] K. Kristinnson and G. A. Dumont, "System identification and control using genetic algorithms," IEEE Trans. System, Man, Cybern., vol. 22, pp. 1033–1046, Sept.-Oct. 1992.