Intelligent Motor Control Using Advanced Bacterial Foraging Combined With Immune Algorithm

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Abstract

This paper suggests advanced bacterial foraging strategy using membership function of fuzzy logic and clonal selection of immune system. Bacteria foraging based optimal solution is defined by the positions of each member in the population of the *S* bacteria at the *j*th chemotactic step, *k*th reproduction step, and *l*th elimination-dispersal event. Therefore, chemotactic step is important to have an optimal solution in system. Up to now, a foraging strategy uses fixed chemotactic step. This paper introduces clonal selection of immune algorithm and fuzzy logic into bacterial foraging to enhance running speed and patch of optimal condition (e.g., group of objective with conditions). This approach provides us with novel hybrid model based on foraging behavior and clonal selection for a higher running time and optimal solution.

1. introduction

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. Natural selection are more likely to apply reproductive success to have an optimal solution. 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. 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. 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 BF (Bacterial Foraging), and CL (Clonal Selection) and fuzzy logic. Finally, we focus on evidence for the proposed hybrid system for indirect vector control of induction motor.

2. Hybrid Optimization Based on Bacteria Foraging and Clonal Selection

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

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

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 $P_c^i(\phi)$, $i=1, 2, \ldots, S$, to model the cell-to-cell signaling via an attractant and a repellant is represented by

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

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 Vector Control Using Advanced Bacteria Foraging Based on Fuzzy Logic and Immune Algorithm

3.1 Vector Control System of Induction Motor

As the vector controlled induction machine is assumed to be current fed from an ideal current controlled PWM inverter, operation with constant, rated flux command would be discussed. As the indirect vector controller is the scheme composed of the appropriate decoupling circuit for each of the three orientation possibilities such as stator, air-gap, and rotor flux oriented control, it incorporates only PI speed controller. Decoupling circuits neglect iron loss, magnetic saturation and resistance variations and have the well-known form, representation of the induction machine, in terms of space vectors.

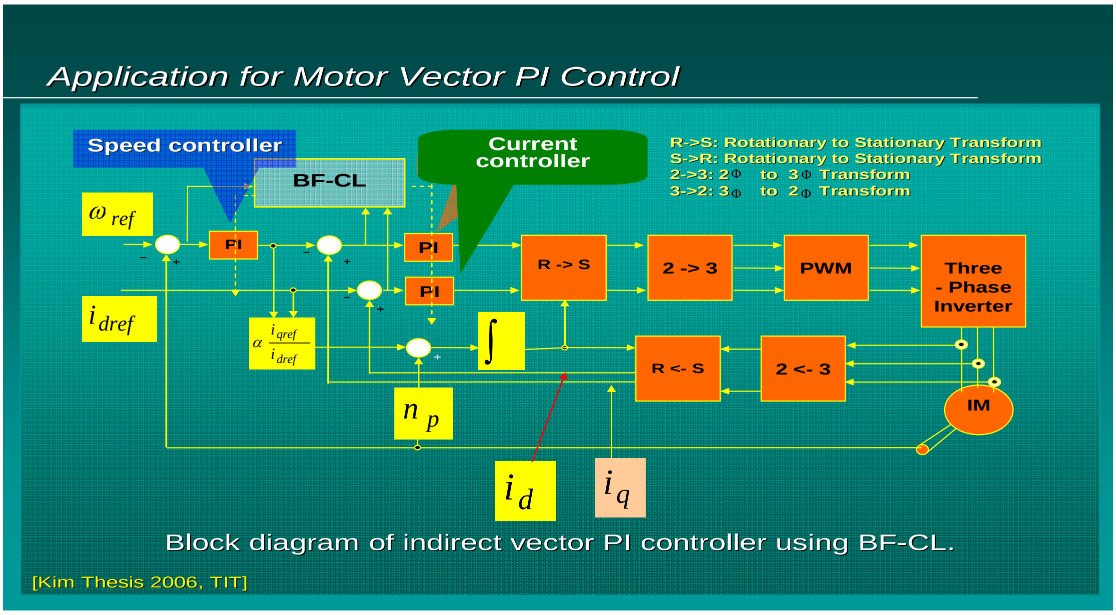

Fig. 1. Block diagram of indirect vector PI controller using advanced BF (bacterial foraging) based on fuzzy logic and clonal selection.

That is, the indirect vector control system neglects the core loss. The electrical torque in an induction machine can be expressed as:

$$T_e = \frac{3}{2}\frac{P}{2}\frac{L_m}{L_r}\lambda^e_{dr} i^e_{qs}\,, \tag{3}$$

where, rotor flux instantaneous speed ω_e, $\lambda^e_r = \lambda^e_{dr} + j\lambda^e_{qr} = \lambda^e_{dr}$, $\lambda^e_{qr} = 0$, $i^e_{qs} = -\frac{L_r}{L_m} i^e_{qr}$. The slip equations for an induction motor in an arbitrary synchronously rotating reference frame are given by:

$$\omega_e - \omega_r = \omega_{sl} = -\frac{R_r i^e_{qr}}{\lambda^e_{dr}} = \frac{R_r}{\lambda^e_{dr}}\frac{L_m}{L_r} i^e_{qs} = \left[\left(1+p\frac{L_r}{R_r}\right)\frac{1}{i^e_{ds}}\right]\frac{R_r}{L_r} i^e_{qs}\,. \tag{4}$$

where, i^e_{qs} is torque current, i^e_{ds} is flux current. When i^e_{ds} and i^e_{qs} is decided by ω_{sl}, rotor flux position θ_e is given by:

$$\theta_e = \int_0^t \omega_e d\tau = \int_0^t (\omega_r + w_{sl}) d\tau \tag{5}$$

In indirect vector control, stator current and slip angle ω_{sl} through θ_e is controlled, then $\lambda^e_{qr} = 0$ become [2].

3.2 BF-CL based Optimization Tuning of PI Controller for Induction Motor

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].

[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.

Table 1. Parameter ranges for Learning of bacteria foraging.

Parameters	Value
N: The No. of BF group	100
N_c : The No. of chemotaxis loop	300
N_{re} : The No. of reproduction steps	2
N_{ed} : The number of elimination-dispersal events	5
P_{ed} : elimination-dispersal with probability	0.5
T: The No. of clones	5
T_m: Probability of crossover of clone	0.25
A_m^* : Gain margin of plant	2.5
ϕ_m^* : Phase margin of plant	45

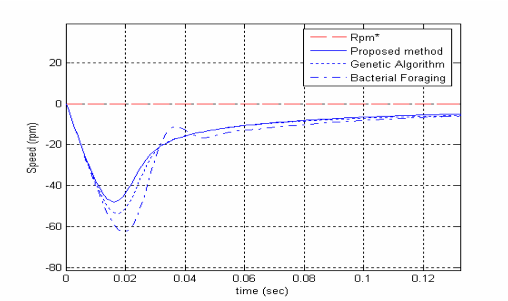

Fig. 3. Speed tracking of indirect vector PI controller (time : 0~0.13 sec).

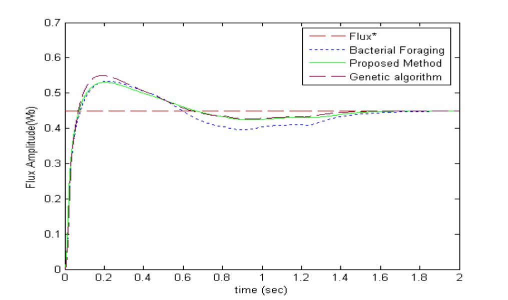

Fig. 4. Flux amplitude tracking of indirect vector PI controller.

[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.

In bacterial foraging strategy, because the number of elimination-dispersal events and, for each elimination-dispersal event, each bacterium in the population is subjected to elimination-dispersal (death, then random placement of a new bacterium at a random location on the optimization domain) with probability, bacterium swim straight alternatively running at 10–20 [microsec] and tumbling. When the flagella rotate clockwise and counterclockwise, they operate as propellers and hence an E. Coli may run or tumble and search avoid unfavorable environments. The objective is simply to capture the gross characteristics of chemotactic hillclimbing and swarming for optimal solution.
Fig. 2 represents computation procedure of optimal solution based on BF-CL learning and Table 1 illustrates parameter ranges for learning of bacteria foraging. Fig. 3 shows speed tracking of indirect vector PI controller (time: 0~0.13 sec) and Fig. 4 means flux amplitude tracking of indirect vector PI controller. Fig. 5 is search process for optimal parameters of PI controller using BF-CL suggested in this paper. Table 2 represents comparison of PI parameters by each method (BF, GA, Proposed algorithm).

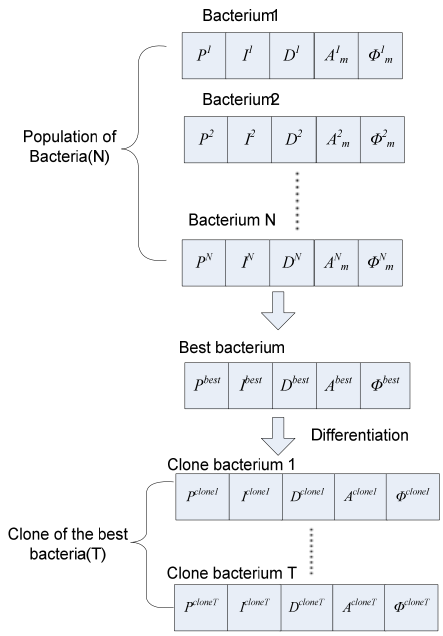

Fig. 2. Computation procedure of optimal solution based on BF-CL learning.

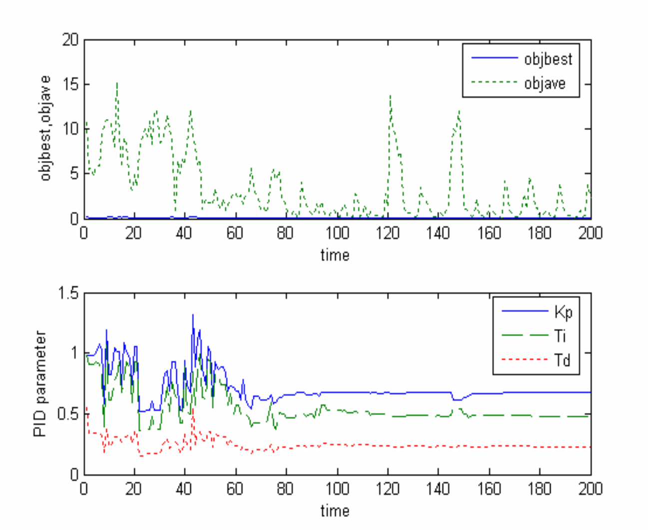

Fig. 5. Search process for optimal parameters BF-CL.

4. 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. GA has also been used to optimize nonlinear system strategies but it might be local optimized. This paper suggests the advanced hybrid system consisting of BF (Bacterial foraging Algorithm) and CL (Clonal Selection) for PID controller tuning of induction motor control system. Ref [13] depicts characteristic to variation of step size when generations from 1 to 50 and from 270 to 300, respectively. From Ref [13], the bigger step size, the convergence is faster. Ref [13] are also showing relationship between objective function and the number of generations in different chemotactic steps. When the chemotactic step is smaller, the objective function has a faster convergence with a small generator. In Ref [13] is showing characteristics between objective function and generators for different life times Ns of bacteria in the hybrid system, GA-BF. In BF system, chemotactic step, total number of chemotactic reaction of bacteria, step size, basic unit for movement of bacteria Ns, the number of critical reaction S, the number of bacteria G, generations Mu, mutation Cr, and crossover is very important for learning condition.

Therefore, this paper extends variable step size against environmental condition using fuzzy logic and clonal selection to illustrate characteristics. 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).

Table 2. 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

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.

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