Chemotaxis for Controller Tuning

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ABSTRACT: Chemotaxis algorithm is based on analogy to the way bacteria react to chemoattractants in concentration gradients. This idea has been used in solving optimization problems. This paper outlines how the method could be applied in controller tuning. It uses a simple one-dimensional algorithm for tuning the gain in the PI-controller controlling two different processes. The first one is a stable first order process and the second one a more complicated third order process that becomes unstable with high enough controller gain. The results are promising, but further work is required to apply the method in actual process control. The real-time application might also face some time limitations, because in some cases excessive number of iterations is required.

KEYWORDS: tuning, nature-inspired systems, Chemotaxis, optimization

INTRODUCTION

Chemotaxis algorithm is based on analogy to the way bacteria react to chemoattractants in concentration gradients. It was pioneered by Bremermann and two of his papers are frequently referenced in this connection [1,2]. Bacteria are single-cell organisms, one of the simplest forms of life on earth. It has been found that they receive information about their environment and use this information efficiently to survive. Optimization algorithms may also be viewed as entities that gather information on the optimization problem and then use this information to reach the optimum. Bacterial chemotaxis offers a starting point for constructing an optimization algorithm. Two types of algorithms exist: one resembles the well-known ant and bee algorithms in the sense of bacteria swarming and social foraging [8]. The other looks bacteria as individuals. Some authors include the mimicking of foraging behaviour of other animals (silkworm moth, dungle bee) in the group of chemotaxis algorithms [10]. On the other hand, the negative chemotaxis means the individual's or swarm's behaviour to, let us say, a toxic signal.

The term taxis refers to the locomotory response of a cell to its environment [7]. In a taxis, a cell changes both its direction and the duration of the next step. The tactic response requires some directional information from the environment that bacteria obtain by comparing an environmental property at two different time steps. If the tactic response is related to information about chemical concentrations, it is called chemotaxis. Bacterial chemotaxis of E. coli is one of the best understood [3, 8]. Lebiedz and Maurer [4] describe numerical simulations and optimal control of E. coli bacterial chemotaxis. They use parabolic PDE model of reaction diffusion type containing two variables, the cell density and the concentration of the chemotactically active species (chemoattractant), which triggers cell movement in the uphill direction of its own gradient. Passino [8] studies a variety of bacterial swarming and social foraging behaviour and discusses the control system based on the E. coli. The distributed optimization algorithm is applied to a simple multiple-extremum function minimization. Also, the potential use of social foraging to adaptive controllers and co-operative control strategies is studied.

Some early references are in Müller et al. [7], and they also introduce a new approach for using bacterial chemotaxis in optimization. They concentrate on studying microscopic models that consider the chemotaxis of a single bacterium instead of macroscopic models that analyze the movement of bacteria colonies. They use the original biological model and present a simple (2-D) optimization algorithm, which is evaluated on a set of standard test problems. This algorithm is upgraded for n-dimensional case and several other features are added. Its performance is compared to other techniques and it is also used in the inverse airfoil design. Styer and Vemuri [12] have compared adaptive critic algorithms and Chemotaxis algorithm in a typical control engineering test process, a cart and pole system. They found the methods quite equal and the Chemotaxis algorithm was better in generalising the controls. Ramos et al. [9] have also presented a similar algorithm that they call artificial bacterial foraging algorithm and tested it with several conventional test functions. Canright et al. [3] have reported on applying a negative chemotaxis-inspired algorithm for load balancing in networks. Russell et al. [10] have compared three chemotaxis algorithms for the control of the chemical plume tracking robot. They found that E. coli-inspired algorithm, even though simple, had some serious limitations, and another chemotaxis algorithm, that they "silkworm moth algorithm", compared the best. Marques et al. [6] have also tested similar approaches in the connection of the electronic nose system. Li and Jiang [5] have reported on integration of Simulated Annealing, Genetic Algorithm and Chemotaxis Algorithm to a new method that outperforms each individual approach.

CHEMOTAXIS ALGORITHM

There are many ways to convert the controller tuning to an optimization problem. Here, the target is to minimize the difference (the control error) between the process output y(t) and its set point r(t) by tuning the controller. Controller performance in this sense is measured using different performance indices and in this case the Integral Absolute Error is applied.

This paper uses a simple one-dimensional algorithm for searching the optimal gain in the PI-controller controlling two different processes. The first one is a stable first order process and the second one a more complicated third order process that becomes unstable with high enough controller gain. The algorithm proceeds in the following way and it is a modification of the one presented in [11]:

1. Choose the initial value for K_C. Two alternatives have been tested for both processes. This is done in order to study the sensitivity of the method for the initial value.

2. Simulate the controlled process for the unit step change in the set point.

   R(s)=1/s.

   Simulation time runs from 0 to 20 seconds.

3. Calculate the performance index, in this case Integral Absolute Error, IAE.

   $$IAE = \int_0^{20} |e| \, dt$$

   $$e(t) = y(t) - r(t)$$

   Above, y(t) is the measured process output. Calculate the new value for K_C.

   $$K_C = |K_C + \Delta|$$
   $$\Delta = \sqrt{\sigma^2} d$$

   Above, σ^2 and d are random numbers taken from the normal distribution with zero mean and variance 1.

4. Simulate the process again.

5. Calculate the new value for the performance index.

6. Depending on that value
   If IAE(i)<IAE(i-1)
   Change K_C to the same direction and go to 4
   If IAE(i)≥IAE(i-1) return the previous K_C and go to 3.

7. Repeat from point 4 for N times. N must be chosen big enough to guarantee that the optimal value is found. This value depends on the process and two different values have been used for both processes.

8. Register the minimum of the performance index and the corresponding K_C. Because of the stochastic behaviour, each test is repeated ten times and the average values are used. See Tables 1 and 2.

The method is tested using simulations in Matlab® Simulink® environment. The Chemotaxis algorithm is written a m-file and the process models are Simulink models.

THE PROCESS AND THE CONTROLLER

Two simple, but different processes are studied. A simple first order process is considered

$$G(s) = \frac{K}{Ts+1}$$

It is controlled by a PI-controller

$$G_C(s) = K_C(K_p + \frac{K_I}{s})$$

K_C is the control parameter to be optimized using a Chemotaxis algorithm (the overall gain) and other process and controller parameters are as follows

$K=1$
$T=1$
$K_p=1$
$K_I=2$.

Simulation reveals easily, how this system behaves when the overall gain K_C is increased. Figure 1 tells that the value of IAE index does not remarkably decrease after the gain has reached the level of 30-50. In this case, the stopping criterion shown above is not the best possible.

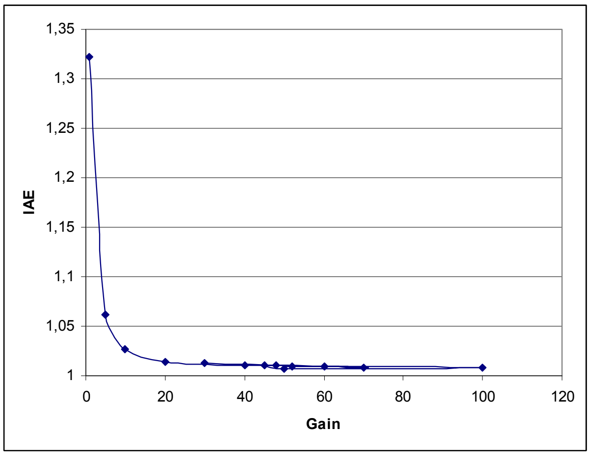

Fig. 1. The dependence of IAE index on the controller gain in the first process.

Next, a third order process

$$\frac{1}{s^2 + 3s + 3}$$

is studied. It differs from the previous one so that it becomes unstable with high enough overall gain, K_C. This is shown in Fig. 2 and Fig. 3. Fig. 2 tells that the minimum is somewhere close to $K_C=2$. Below this value, the response is getting slower and above approximately 5, the oscillations continue to increase.

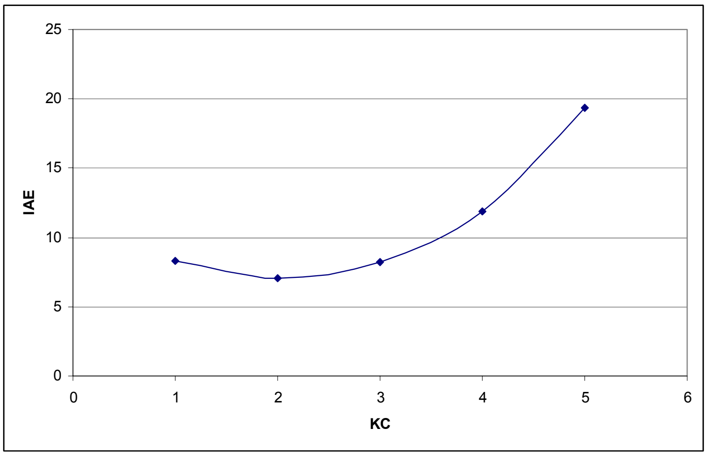

Fig. 2. The dependence of IAE index on the controller gain for the second process.

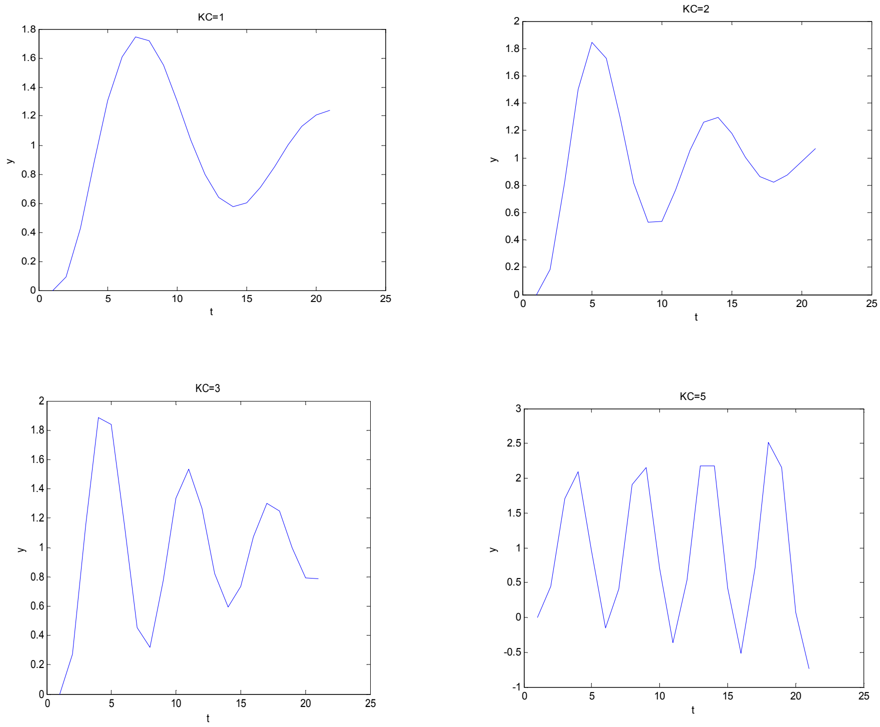

Fig. 3. The responses of the second process when the controller gain increases. Low gain means the slow response and increasing gain too much lead to uncontrolled oscillation.

TEST RESULTS

For the first process, the results after using two iteration times (N=100 and N=1000) and two starting points (K_{CO}=0 and K_{CO}=30) are shown in Table 1. The optimum is reached more accurately with the higher number of iterations and starting from closer to the optimum. The actual values of K_C vary considerably, but the visual inspection of the simulated responses show no big differences (Fig. 4 and Fig. 5). The objective function is not so sensitive for the changes in K_C in this case. However, Table 1 shows that N=100 is too small a value when starting from zero.

Table 1. The results for the first process with two iteration times and two starting points.

$K_C(0)$=0	N=100	N=1000
Average	K_C=15.46, IAE=1.07	K_C=44.63, IAE=1.01
Standard deviation	For K_C 9.67 IAE 0.17	For K_C 8.58 IAE 0.001
KC(0)=30		
Average	K_C=33.2, IAE=1.01	K_C=47.84, IAE=1.01
Standard deviation	For K_C 2.28 IAE 0.002	For K_C 7.25 IAE 0.001

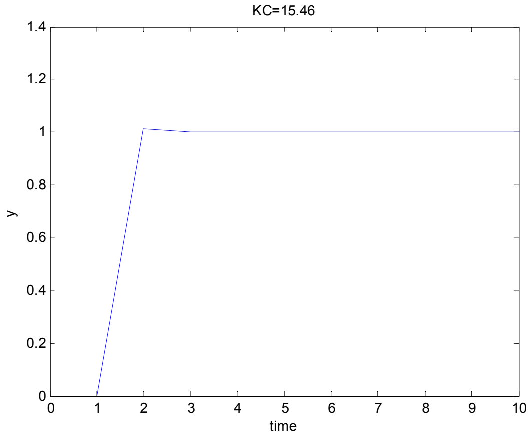

Fig. 4. The response with the small value of the controller gain.

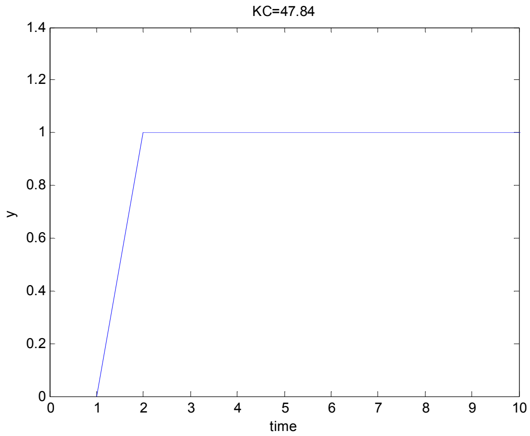

Fig. 5. The response with the high value of the controller gain.

For the second process, the results after using two iteration times (N=50 and N=100) and two starting points (K_{CO}=0 and K_{CO}=5) are shown in Table 2. The optimum is reached more accurately with the higher number of iterations and starting from zero. The actual values of K_C and IAE, however, vary only little in all cases. In this case, a clear minimum exists and it seems to be easier to find compared with the first process.

Table 2. The results for the second process with two iteration times and two starting points.

$K_C(0)$=0	N=50	N=100
Average	K_C=2.20, IAE=7.01	K_C=2.22, IAE=7.0
Standard deviation	For K_C 0.09 IAE 0.02	For K_C 0.01 IAE 0.002
KC(0)=5		
Average	K_C=2.20, IAE=7.01	K_C=2.23, IAE=7.00
Standard deviation	For K_C 0.09 IAE 0.01	For K_C 0.01 IAE 0.01

CONCLUSIONS

This paper has shown the first results of applying Chemotaxis algorithm for the controller tuning. Two considerably simple "toy processes" were chosen and the algorithm was tested in Matlab® Simulink® environment. The first process, even the simpler one, seemed to be more difficult for the algorithm. This could be improved by using another stopping criterion. Anyway, the process performance in this case was not so sensitive for the controller tuning. The results are promising, but there is still a lot of work left for the actual application in process control. The high number of iterations required in some cases cause worry for the on-line controller tuning, especially for processes with fast response times.

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