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Bat algorithm in terms of generalized nets

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Abstract: The generalized net theory is used here to model a meta-heuristics, named Bat algorithm (BA). The BA is based on the echolocation behaviour of microbats with varying pulse rates of emission and loudness. The proposed generalized net model provides the opportunity to describe the logic of BA, executing the algorithm procedure basic steps and realizing an optimal search.
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1 Introduction

The use of Generalized Nets (GNs) [2, 3, 5] affords the different opportunities for i) on-line applications; ii) searching of optimal conditions; iii) learning on the basis of experimental data; iv) control on the basis of expert systems, etc.

Until now the apparatus of GNs has been used as a tool for a description of parallel processes in many areas [8]. The facility of obtaining GN-models demonstrates the flexibility and the efficiency of generalized nets as modelling tools in different fields [4, 6, 7, 9].

In [4] GNs have been used as a tool for modelling of various genetic algorithms. Developed GN-models execute the genetic algorithm procedure performing basic genetic operators [12]. This fact provokes the idea of developing a GN-model of Bat algorithm (BA).

BA is a meta-heuristics based on the echolocation behaviour of bats, i.e. on their ability to find their prey and discriminate between different types of insects even in complete darkness [1]. This algorithm was proposed by Xin-She Yang [13, 14]. The resulting algorithm is simple in concept and at the same time powerful in implementation – it can provide very quick convergence at an early stage of iteration by switching from exploration to exploitation if necessary [10, 13, 14]. A comprehensive review is carried out in [11].

The aim of this study is to describe the meta-heuristic algorithm of BA with a GN-model as a premise for it qualitative learning.

2 Bat algorithm

BA, as proposed by [13, 14], is based on the following idealized rules:

1. All bats use echolocation to sense distance, and they also "know" the difference between food/prey and background barriers.
2. Bats fly randomly with velocity v_i at position x_i with a fixed frequency $f_{\min}$, varying wavelength λ and loudness L_0 to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission r in the range of [0, 1], depending on the proximity of their target.
3. Although the loudness can vary in many ways, for example the loudness could vary from a positive L_0 to a minimum constant value $L_{\min}$.

The new solutions $x_i(t)$ and velocities $v_i(t)$ at time step t are given by [13, 14]:

$$v_i(t) = v_i(t-1) + (x_i(t) - x_*) f_i, \tag{1}$$

$$x_i(t) = x_i(t-1) + v_i(t), \tag{2}$$

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta, \tag{3}$$

where $\beta \in [0, 1]$ is a random vector drawn from a uniform distribution, x_* is the current global best solution which is located after comparing all the solutions among all the n bats, f_i is used to adjust the velocity change.

For the local search part, once a solution is selected among the current best solutions, a new solution for each bat is generated locally using random walk [13, 14]:

$$x_{new} = x_{old} + \eta L_i(t), \tag{4}$$

where $\eta \in [-1, 1]$ is a random number, $L_i(t)$ is the average loudness of all the bats at this time step.

The loudness $L_i(t)$ and the rate $r_i(t)$ of pulse emission have to be updated accordingly as the iterations proceed:

$$\begin{aligned} L_i(t+1) &= \alpha L_i(t), \\ r_i(t+1) &= r_i(0)[1 - \exp(-\gamma t)], \end{aligned} \tag{5}$$

where α and γ are constants, whose choice requires some experimenting.

For any $0 < \alpha < 1$, $0 < \gamma$, we have [13, 14]

$$L_i(t) \to 0,\ r_i(t) \to r_i(0), \text{ as } t \to \infty \tag{6}$$

The loudness $L_i(t)$ and emission rates $r_i(t)$ will be updated only if the new solutions are improved, which means that these bats are moving towards the optimal solution.

3 Generalized net model of Bat algorithm

The GN-model, describing the Bat algorithm, is presented in Figure 1. The token α enters GN through place l_1 with an initial characteristic

"BA parameters: n, N_{gen}, A, r, Q_{min}, Q_{max}, d, Lb, Ub",

where n is the population size; N_{gen} is the number of generations; A is the loudness; r is the pulse rate; Q_{min} and Q_{max} are frequency minimum and maximum; d is the number of dimensions; Lb and Ub are the lower and upper limit/bounds of the search parameters.

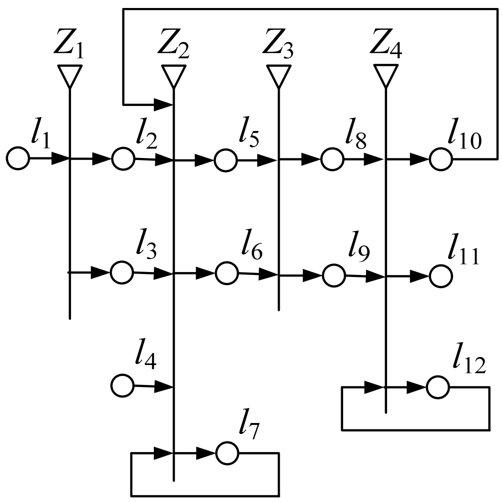

Figure 1: GN-model of Bat algorithm

The form of the first transition of the GN-model is

$$Z_1 = \langle \{l_1\}, \{l_2, l_3\}, r_1, \vee(l_1) \rangle,$$

$$r_1 = \begin{array}{c|cc} & l_2 & l_3 \\ \hline l_1 & true & true \end{array}.$$

The token α is splited in two new tokens ε and χ. In place l_2 the token ε obtains the characteristic

"Q (velocities), v (frequency), Q_{min}, Q_{max}, A, r, Lb, Ub",

where Q = zeros(n, 1) and v = zeros(n, d).

In place l_3 the token χ obtains the characteristic

"*Sol* (solution initialization)",

where $Sol = Lb + (Ub - Lb)\mathrm{rand}(1, d)$.

The token δ enters GN through place l_4 with an initial characteristic

"*Fun* (Objective function $f(x)$)".

The form of the second transition of the GN-model is

$$Z_2 = \langle \{l_2, l_3, l_4, l_7, l_9\}, \{l_5, l_6, l_7\}, r_2, \vee(l_2, l_3, l_4)\rangle,$$

$$r_2 = \begin{array}{c|ccc} & l_5 & l_6 & l_7 \\ \hline l_2 & false & true & false \\ l_3 & true & false & false \\ l_4 & true & false & true \\ l_7 & true & false & false \\ l_9 & false & false & true \end{array}.$$

In place l_5 the tokens χ and δ are combined in a new token γ with the characteristic

"*Fitness* (fitness function), *Fun*, *Sol*",

according to $Fitness(i) = Fun(Sol(i, :))$.

In place l_6 the token ε keeps the same characteristic

"Q, v, Q_{min}, Q_{max}, A, r, Lb, Ub".

In place l_7 the token γ keeps the same characteristic

"*Fitness*, *Fun*, *Sol*".

The form of the third transition of the GN-model is

$$Z_3 = \langle \{l_5, l_6\}, \{l_8, l_9\}, r_3, \vee(l_5, l_6)\rangle,$$

$$r_3 = \begin{array}{c|cc} & l_8 & l_9 \\ \hline l_5 & true & false \\ l_6 & false & true \end{array}.$$

In place l_8 the token γ obtains a characteristic

"*Fitness*, *Fun*, Sol_{best} (current best solution)"

according to
$[f_{min}, I] = \min(Fitness)$;
$Sol_{best} = Sol(I, :)$.

The token ε keeps the same characteristic

"$Q, v, Q_{min}, Q_{max}, A, r, Lb, Ub$"

in place l_9.

The form of the fourth transition of the GN-model is

$$Z_4 = \langle \{l_8, l_9, l_{12}\}, \{l_{10}, l_{11}, l_{12}\}, r_4, \vee(l_8, l_9)\rangle,$$

$$r_4 = \begin{array}{c|ccc} & l_{10} & l_{11} & l_{12} \\ \hline l_8 & false & false & true \\ l_9 & false & false & true \\ l_{12} & W_{12,10} & W_{12,11} & true \end{array},$$

where:

$W_{12,11}$ = "*End of the BA is reached*";
$W_{12,10} = \neg W_{12,11}$.

The token γ obtains the following characteristics:

- in place l_{10} – "$Fitness_{new}, Sol_{new}$";
- in place l_{11} – "$Fitness_{final}, Sol_{final}$";
- in place l_{12} – "$Q_{new}, v_{new}, Fitness_{new}, Sol_{new}$", according to

```
for i = 1:n
      Q_new(i) = Q_min + (Q_min – Q_max)rand;
      v_new(i, :) = v(i,:) + (Sol(i,:) – Sol_best)Q(i);
      Sol_new(i, :) = Sol(i, :) + v(i, :);
      Sol_new(i, :) = check_bounds(Sol_new(i, :), Lb, Ub);
      if rand > r
         Sol_new(i, :) = Sol_best + 0.001randn(1, d);
      end
      Fitness_new = Fun(Sol_new(i, :));
      if (Fitness_new <= Fitness(i)) & (rand < A) ,
          Sol(i, :) = Sol_new(i, :);
          Fitness(i) = Fitness_new;
      end

      if Fitness_new <= f_min,
          Sol_best= Sol_new(i, :)
          f_min = Fitness_new
      end
end
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In this transition a new solution (Sol_{new}) is generated by adjusting frequency and velocities and by flying randomly. If termination condition of the BA is reached the final best solution is obtained (place l_{11}), otherwise the next iteration is performed (place l_{10} and second transition).

4 Conclusion

Generalized nets are preliminary proved to be an appropriate tool for description of the logics of different optimization techniques. Here, a generalized net model of the optimization process based on echolocation behaviour of bats is considered. The generalized net model consists of four transitions and twelve places. Developed model executes the algorithm procedure performing basic steps and realizes an optimal search.

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