P2

Real world problems are often represented as “multimodal” which means multiple global & local optima exist.

For example, the left figure shows the multimodal function, which have several multiple solutions. In detail, the deep red solution indicates the global optimum while the light red solutions indicate the local optima for the minimization problem. The right figure, on the other hand, shows the safe landing site selection in lunar mission as one of real world problems. In this case, we have to find many danger spots (at the red point) where are located on bumpy surface. Like as the multimodal function, the red solution indicates the global best optima and light red solution indicates the local optima from danger spots. For avoiding these danger spots, we would like to know where some danger spots are located as possible as we can.

P3

To find multiple optima which is so-called Niching methods, are proposed by X.Li. Concretely, niching methods are designed by combining evolutionary algorithms with niching scheme. As major niching methods, crowding DE is proposed by Thomsen to replace solutions with similar high-quality solution candidates, and DE with Speciation is proposed by Li to keep solutions away from the nearest neighbor solutions.

However, these methods are not enough to find multiple local optima solutions due to a weak of exploration search. In detail, (1) DE updates the solutions from the current one, that is, the exploitation based search, which is hard to find the other solutions; and (2) the niching methods such as crowing and speciation mechanisms contributes to exploring solutions, but its search is not effective because they simply replace the solutions or move solutions from other solutions.

So we proposed Novelty search-based Bat algorithm combined BA which can adjust the exploitation and the exploration, with Novelty search which can search new solutions where never visited area.

P4

To tackle this problem, we employed Bat algorithm which is one of the evolutionary algorithms and inspired by the bat behavior. BA is superior for adjusting exploitation and exploration search .

As bats approach the global best solution, the loudness decreases while the pulse emission rate increases, to control the search area and the precision of distance to the global best solution.

As shown in this slide, BA consists of 3 search mechanisms, where the first two mechanisms are based on the exploitation search while the third mechanism is based on the exploration search.

In detail, BA updates the gray circle solutions to the orange circle solution candidates toward the star marked global best solution, and searches the solutions around the global best solution represented by the orange dashed-line area as the exploitation search. BA also searches new areas by the random search as the exploration search.

P5

while NS is also employed because it searches unvisited area, which has a potential of finding new solutions.

An example of the num of nearest neighbor k=5, the sparseness function is calculated by this equation for the target solution. In this case, the target solution get the red norm vector as shown in right figure.

P6

This is the BA flowchart which is divided in the following six steps.

In step 1, the population is initialized as well as the parameters.

(For each bat, the three solution candidates are generated)

In step 2, new solution candidates are generated toward the global best solution

In step 3, other new solution candidates are generated around a global best solution as the local search.

In step 4, in addition to them, other new solution candidates are explored as the random search in the search space.

In step 5, if one of three new solution candidates is better than the current solution, the current solution is replaced by better new solution candidate.

Finally, return to the step 2.

P7,8

In step1, the population is randomly generated by the equation as shown in the right figure.

In detail, the i-th solution, x\_i is generated within the upper bound of the search space (x\_ub) and the lower bound of the search space (x\_lb). Here, x2 = x\* (anime)

P9

After that, In step 2, new solution candidates are generated toward the global best solution.

For example, x\_1 moves to right, x\_3 moves the down, and x\_4 moves left to be close to the global best solution. Such moved solutions become new solution candidates. Note that x\_2 does not move because the x\_2 is the global best solution, (that is, the distance to the global best solution is 0.)

P10

In step 3, if the pulse emission rate r is less than random value, other new solution candidates are generated around the global best solution as the local search.

In detail, the local solution of x\_i is generated around x\_\* by the equation as shown in this figure.

is the window of x\_\* which means that solution candidates x\_loc\_i are generated within this range limited by .

P11

other new solution candidate, x\_rnd\_i is randomly generated in the search space by the equation, which is the same one in step 1.

P12

Then here, if the loudness value is larger than random value and the fitness value of candidates are better than the current solution, the new one is overwritten as the current solution. Moreover, the loudness value goes down and the pulse emission rate rises up in contrast.

P13

After this first iteration, these solutions come to approach the global best solution again and again. Then, converge to the global optima.

P14

This is the BA and NSBA flowchart.

In our proposed method, we made 2 changes. The one change is to extend BA with Novelty search for finding many optima which never found. The other one is to generate new solution candidates around the personal best solution in the exploitation.

P15

This is the novelty search. When some solutions are crowded in the dense area, the sparseness function rho can keep solution x away from the nearest neighbor solutions mu i. But this function calculates norm vector, so we represented it to vector equation as below. Moreover, we changed this equation independent of parameter k. when solutions already distributed, the vector is calculated almost 0.

P16

In this step from conventional BA to NSBA, we changed global best solution to local best solution.

P17

This mechanism can locate solutions to multiple local optima.

P18

To measure the number of global and local optima by NSBA compared with BA, we employed 2 multimodal functions for minimization. These figures show the 2-dimensional fitness landscape and the contour plot. The global and local optima located in the blue area in both functions. F1 has 1/16, and F2 has 1/120.

P19

To compare BA with NSBA, we employed Found Peaks (FPs) and Peak ratio (PR) as the evaluation criteria. FPs means how many peaks the algorithm found. In this experiment, we defined the peak is found, when Euclidean distance between the peak and the nearest neighbor solution less than threshold dist\_{max}0.1.

And PR means the ratio of FPs.

Parameters are setting as right table.

P20

From F1, BA found just 1 peak and the PR was 5.89%. NSBA found about 7 peaks and the PR was 42.75% (dramatically higher than BA).

From F2, BA also found just 1peak (and the PR was 0.87%), but NSBA found 7.9 peaks and the PR was 6.56%.

NSBA outperformed than BA from this table, but the PR of BA and NSBA were quite small value.

P21

These figure are the solution distribution of BA and NSBA.

The white circle shows solutions at the final iteration.

From case1, BA found only the global optimum, however, NSBA found the global optimum with some local optima around it.

P22

In case2, BA also found only the global optimum. But NSBA found 7 optima including global and local optima.

P23

In conclusion, for searching multiple optima in multimodal optimization, we proposed Novelty search-based Bat algorithm which extends BA with a mechanism to search new solutions where never visited.

We made 2 changes from conventional BA. The one is to extend with Novelty search, and the other is change exploitation around the personal best solution.

As a result of simulations of BA and NSBA, BA just searched a single global optimum, but NSBA could search both a single global optimum and some local optima.

In the future, we will find and keep all global and local optima.