P1

I’m \*\*\* from the university of electro-communications, Japan. Today, I would like to talk about my research entitled by \*\*\*.

P2

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

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 interesting landing site selection in lunar mission as one of real world problems. In this case, we have to find many interesting spots (represented by the red point). Like as the multimodal function, the deep red solution indicates the global best optima while the light red solutions indicate the local optima from interesting spots. For this issue, we want to know the location of interesting spots as much as possible.

P3

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

What should be noted here is that 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.

To tackle this problem, we proposed Novelty search-based Bat algorithm by employing Bat algorithm instead of DE and employing novelty search (以下，NSと略しますが，話すときはnovelty searchと言って下さい) instead of crowing and speciation mechanisms. In particular, BA is employed because it has the exploration search mechanism in addition to the exploitation search mechanism, while NS is also employed because it searches unvisited area, which has a potential of finding new solutions.

To understand BA and NS, let’s start to explain them from the next slide.

P4

Bat algorithm proposed by Yang is one of the evolutionary algorithms and it has the capability of switching exploitation & exploration search mechanism, which is inspired by the bat behavior.

As bats approach a food/prey (corresponding to 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.

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Next, NS proposed by Lehman aims at searching unvisited area, which has a potential of finding new solutions.

This figure shows how the new solution is searched in the case that the num of nearest neighbor k=5. Concretely, the new solution (corresponding to the orange target solution x) is searched by considering the distance to the other solutions (that is, four gray solutions u\_1, u\_2, u\_3, and u\_4).

To find the unvisited area, NS calculates the sparseness of solutions by the following equation, meaning that the solutions are sparse when theρvalue is large. Note that we assume that unvisited area can be searched when the solution becomes sparse.

In this example, the orange target solution x is promoted to be moved to the red solution because theρvalue becomes large by increasing the all of distance to the other four gray solutions.

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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.

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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)

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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 to down, and x\_4 moves to 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.)

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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, x\_\*, as the local search.

In detail, x\_loc\_i, 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 the range of .

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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.

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

After that the loudness value decreases, while the pulse emission rate increases in contrast.

In step 6, return to the step 2.

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Through the cycle of these six steps, the solutions are closed to the global best solution, and finally converge to the global optima.

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This slide adds the NSBA flowchart in the BA flowchart

As you can see, we improve two parts for NSBA.

In detail, the step 2 is improved to introduce Novelty search into BA for finding many optima which has not yet found. The step 3 is also improved to generate new solution candidates around the personal best solution instead of the around the global best for finding better solutions around the personal best solution.

I will explain these improvements from the next slide.

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In order to find other solutions, the step 2 in NSBA move solutions from dense area to sparse area by NS. Concretely, NSBA calculates the distance vector of solution by this function, where this part corresponds to the sparseness function. What should be noted hear is that this equation is modified from the norm (the absolute value of x\_j – u\_i) to the vector (x\_j – x\_i) to determine the moving direction and is also modified to adjust the moving distance by dividing it with the square of the norm.

From this equation, for example, x\_1 moves to left up, x\_2 moves to left down, x\_3 moves up left, and x\_4 moves to right down in order to move from dense area to sparse area. Note that the parameter k is independently determined by the distance, the moving distance is calculated almost 0 when solutions already distributed.

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To keep and improve the multiple solutions, the step 3 in NSBA search the solution around the personal best solution instead of the global best solution.

From this modification, for example, the x\_loc\_1, the local solution of x\_1 is generated around x\_1 within the range of . The local solution of x\_2 is also generated around x\_2 within the range of , and so on.

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This mechanism can locate solutions to multiple local optima.

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To investigate the effectiveness of NSBA compared with BA, we employ 2 multimodal functions for minimization. These figures show the 2-dimensional fitness landscape and the contour plot. The left figure shows the Griewank Function represented by this equation, while the right figure shows the Rastrigin function represented by this equation.

(As the characteristics of these functions, Griewank Function has …. while Rastrigin function has…)

In detail, the search space in F1 is the range between -10 to 10 in each dimension and the global best solution is 0, while the search space in F2 is the range between -5 to 51in each dimension and the global best solution is also 0.

Since the blue area indicates the good solution area while the yellow area indicates the bad solution area in this figure, the global and local optima are located in the blue area in both functions. In detail, F1 has 1/16, and F2 has 1/120. The global optimum of both function is located as the center of this function and the better local optima are located around the global optimum (as shown in this figure).

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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.

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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.

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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.

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

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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.