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Homework Assignment

Use the Particle Swarm Optimization Algorithm to optimize the Rastrigin Function

The Rastrigin function is a non-convex function used as a benchmark problem in optimization due to its complex topological characteristics with many local minima, making it a challenge for optimization algorithms to find the global minimum.

$$f(\mathbf{x})=An+\sum_{i=1}^{n}[x_i^2-A\cos(2\pi x_i)]$$

where:
n is the dimension of the input **x,**
A is a constant usually set to 10,
x_i is the ith component of the position vector x.

Experimental Methodology

This experiment is designed to understand the influence of PSO variables and attributes on the optimization of the Rastrigin function, a non-linear function widely used as a benchmark in global optimization due to its complex local peak profile. Experiments are carried out in three dimensions of the search space (2D, 3D, and 4D) to test how PSO adapts to increasing complexity.

Experimental Parameters

Number of Particles:
Experiments were carried out with 30 and 50 particles to see the effect of population size on achieving the optimal solution.

Number of Iterations:
Experiments were carried out with 100 and 250 iterations to evaluate the convergence speed of the algorithm in the short and long term.

Static vs. Static Parameters Dynamic:
Two sets of experiments are performed; one with static PSO parameters and one with parameters that dynamically change over time. These include inertial weights (w), cognitive factors (c1), and social factors (c2).

Experimental Configuration

For static experiments, the parameters w, c1, and c2 are set to fixed values throughout the entire optimization process.

In dynamic experiments, the values of w, c1, and c2 adapt from the beginning to the end of the experiment, allowing for more flexible search strategies.

Results and Discussion

The following is a table of results from the first experiment:

Table 1. Static Params Results for 2D

Particles	Iterations	Best Position	Best Value
30	100	[-0.,-0.]	8.62e-11
50	100	[-0., 0.]	0.00e+00
30	250	[-0., 0.]	0.00e+00
50	250	[-0.,-0.]	0.00e+00

Table 2. Static Params Results for 3D

Particles	Iterations	Best Position	Best Value
30	100	[-0.99496,-0. ,-0.]	9.95e-01
50	100	[0.,-0., 0.]	1.67e-10
30	250	[0.,-0.,-0.]	0.00e+00
50	250	[0.,-0., 0.]	0.00e+00

Table 3. Static Params Results for 4D

Particles	Iterations	Best Position	Best Value
30	100	[-0.99497,-0.00007,-0. ,-0.00005]	9.95e-01
50	100	[1.00194,0.0061 ,0.01862,0.0115]	1.11e+00
30	250	[-0., 0., 0., 0.]	0.00e+00
50	250	[0.,-0.,-0.,-0.]	2.11e-12

Effect of Number of Particles and Iterations

2D: Increasing the number of particles and iterations contributes significantly to the convergence of the optimal solution in 2D experiments. Based on **Table 1** (Results with Static Parameters for 2D) and **Table 4** (Results with Dynamic Parameters for 2D), experiments using 50 particles and 250 iterations achieved a "Best Value" value close to zero, indicating the effectiveness of PSO in finding the global minimum of the Rastrigin function. A comparison between the two also indicates that the use of dynamic parameters can provide slightly more efficient convergence, especially in certain configurations.

3D and 4D: Just as in the 2D case, experiments in 3D and 4D dimensions show that increasing the number of particles and iterations significantly increases the algorithm's chances of finding the optimal solution. This is especially visible in 4D experiments, where the additional complexity of the solution space makes optimization more challenging. **Table 3** (Results with Static Parameters for 4D) and **Table 6** (Results with Dynamic Parameters for 4D) highlight that the experiment with 50 particles and 250 iterations achieved very low "Best Value" values, indicating success in approaching the optimal solution.

Table 4. Dynamic Params Results for 2D

Particles	Iterations	Best Position	Best Value
30	100	[0.,0.]	2.48e-09
50	100	[0.00001,0.]	9.61e-09
30	250	[0.,-0.]	0.00e+00
50	250	[-0., 0.]	0.00e+00

Table 5. Dynamic Params Results for 3D

Particles	Iterations	Best Position	Best Value
30	100	[0.00012,0.00067,0.00151]	5.42e-04
50	100	[-0.00002,-0.00021,-0.00022]	1.85e-05
30	250	[0. ,0. ,0.00002]	1.13e-07
50	250	[-0.,-0.,-0.]	5.89e-09

Table 6. Dynamic Params Results for 4D

Particles	Iterations	Best Position	Best Value
30	100	[0.00671,-0.97156, 1.01699,-0.98817]	3.21
50	100	[0.99436,-0.00068, 0.0023 , 0.00653]	1.00
30	250	[0.00037,-0.00008, 0.00006,-0.0001]	3.12e-05
50	250	[-0.00004,-0.99479,-0.00001,-0.00002]	0.995

Static vs. Static Dynamic

Dynamic Parameter Performance: In general, dynamic parameters show an increase in the ability to find better solutions or with faster convergence, especially in higher dimensions. This suggests that parameter adaptation over time can help PSO overcome local peaks and improve search space exploration. Comparison between **Table 2** and **Table 5** (for 3D) and **Table 3** and **Table 6** (for 4D) shows that the use of dynamic parameters tends to produce lower "Best Value" values compared to static settings, confirming the effectiveness of the parameter adaptation strategy.

Comparison in Different Dimensions: Data analysis from **Tables 1** to **Table 6** shows that significant improvements were seen in experiments with dynamic parameters in all tested dimensions. This is particularly impactful in 4D experiments, where the dynamic strategy is very effective in improving particle performance and achieving lower "Best Value" values compared to the static setup, indicating that dynamic parameters provide additional advantages in the face of higher complexity of the solution space.

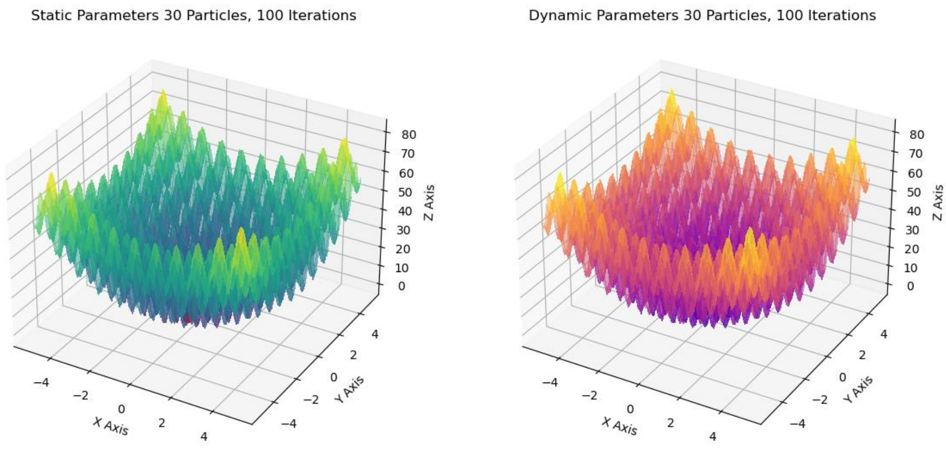

Figure 1. Experiments 30 Particles and 100 Iterarions

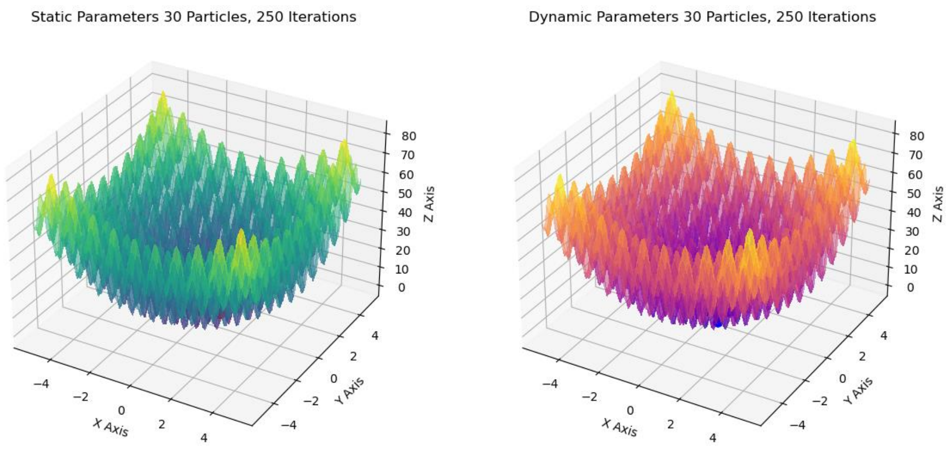

Figure 2. Experiments 30 Particles and 250 Iterarions

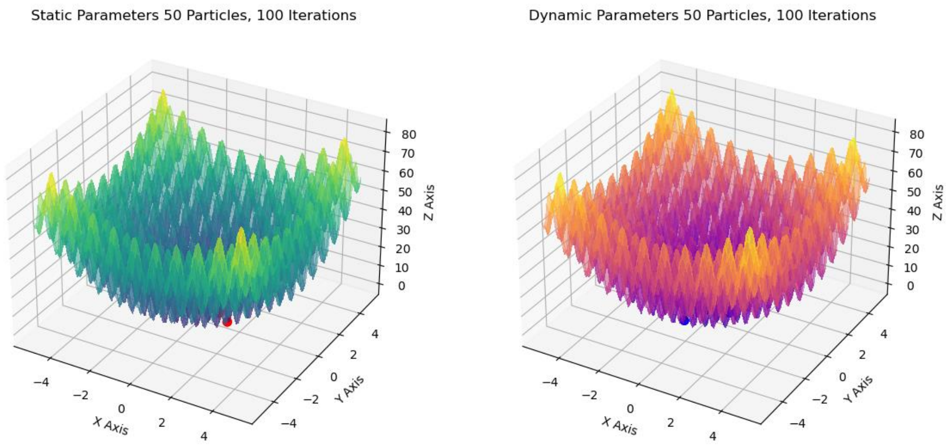

Figure 3. Experiments 50 Particles and 100 Iterarions

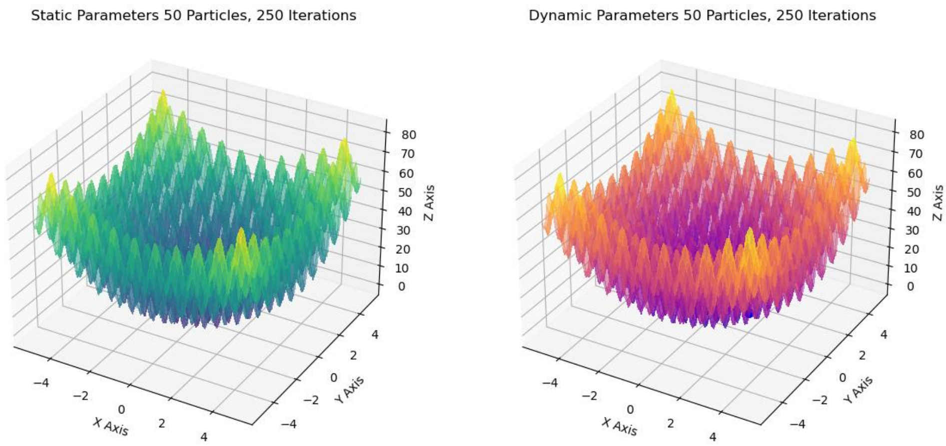

Figure 4. Experiments 50 Particles and 250 Iterarions

Conclusion

These experiments show that PSO, with both static and dynamic parameters, is an effective tool for optimization of the Rastrigin function in multiple dimensions. Dynamic tuning of parameters shows potential in improving optimization performance, especially in more complex search conditions. These findings emphasize the importance of appropriate parameter selection and strategy adaptation in the PSO algorithm to address various optimization challenges.