Visualizing Swarm Behavior with a Particle Density Map

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ABSTRACT

In general, when a problem of high dimension is solved with particle swarm optimization (PSO), a large number of particles is used. However, it is quite difficult to understand this method's search process. To address this, the best known solutions of PSO were fixed as the center point, after which the solutions were reduced to 2 dimensions using Sammon mapping and the search process was visualized using a heatmap. As a result, the PSO process of searching for various optimization functions was able to be understood intuitively, and PSOs possessing different parameters could be compared

CCS CONCEPTS

• **Software and its engineering → Search-based software engineering**;

KEYWORDS

Particle Swarm Optimization, Heatmap, Visualization

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1 INTRODUCTION

The particle swarm optimization (PSO) algorithm [1] proposed by Eberhart and Kennedy in 1995 was developed by analyzing the social behavior patterns of animals such as flocks of birds or schools of fish. Each particle is defined based on swarm theory, and the method is advantageous in that it can obtain a convergence value similar to that of a genetic algorithm (GA), which applies principles of the concept of evolution. Furthermore, because less computation is required than by the use of a GA, PSO can achieve fast execution speeds, allowing it to be applied to many areas and problems that are difficult to solve using conventional algorithms. However, because of the difficulty involved in understanding the search process of such a problem, the analysis was also difficult. To understand this, Kim et al. [2] visualized a search process for PSO consisting of 20 particles; however, because the optimization search process for difficult PSO problems consisted of too many particles, understanding the actual PSO process remained limited. Furthermore, because the locations of the best-known solutions moved randomly, it was difficult to compare search processes that executed independently. To address this issue, this study fixed the best-known solutions as the center points of the projection space, allowing the search process in the actual space to be easily understood and compared. Moreover, use of a heatmap facilitated visualization regardless of the number of particles.

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2 RELATED WORK

2.1 Particle Swarm Optimization

The PSO algorithm is an optimization algorithm that was inspired by the movements of social groups. The term "swarm" refers to all of the particles. A computer stores the historical optima of the swarm and the historical optima of each individual.

$$v_{i+1} \leftarrow w \cdot v_i + c_1 \cdot rand \cdot (b_i - x_i) + c_2 \cdot rand \cdot (g - x_i)$$
$$x_{i+1} \leftarrow x_i + v_{i+1}$$

where w, c_1, c_2 are constants, and $rand$ is a random number between 0 and 1. B_i is the last optimal point of the individual, and g is the last optimum point of the group. Each particle searches for the next point using the optimal point of the individual and the optimal point of the cluster, and performs the optimization while newly updating.

2.2 Variant Sammon Mapping

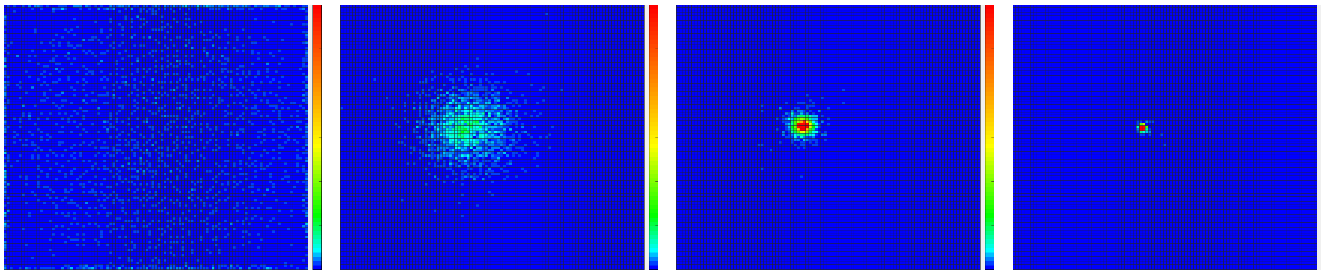
Sammon mapping is an algorithm that projects high-dimensional data into a lower dimension by preserving the distance as much as possible.

$$\frac{1}{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \delta_{ij}} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{(\delta_{ij} - d_{ij})^2}{\delta_{ij}}$$

where δ_{ij} is a distance between the ith and jth objects in the original space, and δ_{ij} is the distance after projection. The Sammon mapping algorithm aims to minimize the above equation, known as the Sammon stress equation, using gradient decent. Kim et al. [2] calculated the initial position using the Sammon mapping, after which the projection of the particle in the current generation was fixed, and the projection of the particle in the next generation was calculated using the Sammon mapping. By repeating this process, continuous projection data for every generation could be obtained. In this study, high-dimensional data were projected to 2-dimensional space using this method.

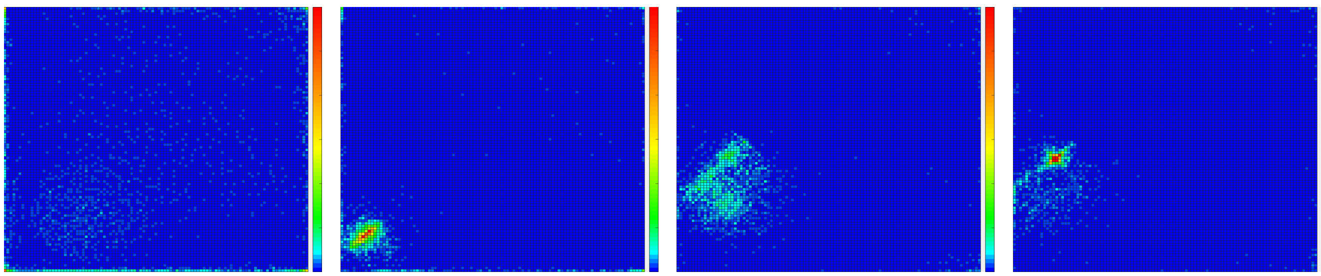
3 NEW APPROACH

In this section, a new visualization method is described. The best-known solutions of the optimization function are fixed as the center points of the projection space, after which a projection is performed



(a) Initial particles **(b) Intermediate particles** **(c) Intermediate particles** **(d) Final particles**

Figure 1: Visualization of Rastrign function



(a) Initial particles **(b) Intermediate particles** **(c) Intermediate particles** **(d) Final particles**

Figure 2: Visualization of Schwefel function

using the variant Sammon mapping described in Section 2.2. Because the best-known solutions are fixed as the center points, the results of searching with different parameters can be compared to one another.

To express the number of particles, a heatmap was used. The heatmap represents data with colors. In this case, the colors blue, cyan, green, yellow, and red were used. By placing divisions between the sections, data of low density could be distinguished. The heatmap allows particles to be distinguished even if they overlap, permitting an infinite number of particles to be visualized. Furthermore, by calculating the middle frame by linear interpolation between intervals in the heatmap, continuous movements could be shown. We rendered the heatmap using MatLab.

4 SIMULATION

The Rastrigin function and Schwefel function [3] were used as the optimization functions for visualization. These two functions serve as representative non-linear optimization problems, with the Rastrigin function being a problem of mid-level difficulty and the Schwefel function being a very difficult problem.

The parameters of the PSO algorithm were as follows: w: 0.9, c_1: 0.5, and c_2: 0.3. Twenty dimensions and 2,000 particles were used. Fig. 1 shows the search process that optimizes the Rastrigin function, from which it can be observed that all particles arrive at their optimal locations. Fig. 2 shows the search process for the Schwefel function. In Fig. 2(b), convergences to local optima are shown. In the work by Kim et al. [2], the process does not continue after convergence to local optima. In this paper, however, instead of stopping at the local optima, shown in Fig. 2(b), new local optima are searched, shown in Fig. 2(c), and convergences are performed at the new local optima, which is shown in Fig. 2(d). A video of the entire experiment, as well as comparisons, can be viewed online at the following URL: https://bit.ly/2DeqkQt

5 CONCLUSION

To understand the PSO algorithm search process that optimizes a difficult problem of high dimensionality using a large number of particles, we visualized the process with a heatmap. The best-known solutions of each function were fixed as the center points, and density of the data was used as the parameter visualized by the heatmap.

Consequently, the motion of the swarm was confirmed, unlike existing conventional studies, and it was seen that new local optima were continuously sought instead of continuously converging to local optima. Furthermore, this allowed the PSO search process for different combinations of parameters to be compared.

A future study may consider other projection methods, such as t-SNE, instead of Sammon mapping, which would cause different visualization results to be obtained.

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REFERENCES

[1] Russell Eberhart and James Kennedy. 1995. A new optimizer using particle swarm theory. In *Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on*. IEEE, 39–43.

[2] Yong-Hyuk Kim, Kang Hoon Lee, and Yourim Yoon. 2009. Visualizing the search process of particle swarm optimization. In *Proceedings of the 11th Annual conference on Genetic and evolutionary computation*. ACM, 49–56.

[3] Hartmut Pohlheim. 2005. Examples of Objective Functions. (Nov. 2005). Retrieved November 1, 2005 from https://goo.gl/dLhnFd