

# Jellyfish Self-Organizing Pulsation Optimization Algorithm

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**Abstract.** Jellyfish, a representative class of coelenterates, possess unique biological behavioral characteristics that provide new insights into intelligent optimization algorithms. This paper proposes an optimization algorithm based on the self-organizing pulsation behavior of jellyfish (Jellyfish Self-Organizing Pulsation Optimization, JSOPO). This algorithm simulates jellyfish's pulsating propulsion, tentacle sensing, light-sensing buoyancy, and swarm self-organization. By mathematically modeling the jellyfish's behavioral mechanisms, this paper constructs a comprehensive algorithmic formula that not only reflects jellyfish biology but also can be used to solve complex optimization problems. The algorithm does not require experimental data validation; instead, it focuses on mechanism modeling and formula derivation, providing a theoretical foundation for nature-inspired intelligent optimization algorithms.

**Keywords:** Jellyfish, self-organization, pulsating propulsion, heuristic optimization, mathematical model.

## I. Introduction

Heuristic optimization algorithms, as an important method for solving complex optimization problems, are often inspired by the behavioral characteristics of natural organisms, such as flocks of birds, schools of fish, and insects. Jellyfish, as coelenterates that float, prey, and self-organize in the ocean, have unique behaviors that offer new possibilities for algorithm design [1-43]. Jellyfish behavioral characteristics primarily include the following:

Pulsating propulsion: Jellyfish generate propulsion through the pulsation of their umbrella, enabling them to move through the water.

Tentacle sensing and predation: Jellyfish tentacles can sense the status of surrounding prey and neighbors, enabling information exchange.

Light-sensing buoyancy: Jellyfish can sense light sources through their photoreceptors, enabling directional movement.

Swarm self-organizing buoyancy: Jellyfish can maintain their group distribution through repulsion and attraction within a swarm, achieving multi-level buoyancy.

Based on these behavioral characteristics, this paper proposes the Jellyfish Self-Organizing Pulsating Optimization Algorithm (JSOPO). Each behavioral mechanism is described through mathematical formulas, achieving a dynamic balance between global search and local exploitation. This paper focuses on the algorithmic mechanism and mathematical modeling, demonstrating theoretical innovation and interpretability.

## II. Problem Description and Algorithm Modeling

Let the optimization problem be to find the optimal value of the objective function  $f(x)$ , where  $x \in R^D$ ,  $D$  represents the search space dimension, and  $N$  represents the number of jellyfish individuals. Each jellyfish individual is denoted as  $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$ , where  $i = 1, 2, \dots, N$ .

The algorithm updates the individual position by simulating four core jellyfish behaviors: pulsation propulsion, tentacle-sensing information flow, light-sensing buoyancy, and swarm self-organized buoyancy. The mathematical models for each are established below.

## III. Pulsation Propulsion Mechanism

Jellyfish generate propulsion through the pulsation of their umbrella, enhancing their local search capabilities. Assume the pulsation energy of the  $i$ -th jellyfish at time  $t$  is  $E_i(t)$ , and its propulsion force  $F_{pulse\_i}(t)$  can be expressed as:

$$E_i(t) = E_{max} * (f(X_i)/f_{max})^{(\beta)}$$

$$F_{pulse\_i}(t) = \alpha * E_i(t) * (X_{best} - X_i(t)) / \text{Distance}(X_{best}, X_i(t))$$

Where  $E_{max}$  is the maximum pulsation energy,  $\beta$  is the energy fitness index, which controls the propulsion capability of jellyfish with low fitness;  $\alpha$  is the pulsation scaling coefficient;  $X_{best}$  is the current global optimal position; and  $\text{Distance}()$  represents the Euclidean distance or other appropriate metric.

The formula for updating a jellyfish's position is:

$$X_i(t+1) = X_i(t) + F_{pulse\_i}(t)$$

This mechanism ensures that high-fitness jellyfish propel themselves vigorously while low-fitness jellyfish float and conserve energy, achieving a dynamic balance between local search and global exploration.

#### IV. Tentacle-Perceived Information Flow Mechanism

Jellyfish tentacles are not only used for hunting but also for sensing information about their surroundings. To simulate information transmission between jellyfish, an asymmetric information flow matrix  $W$  is defined, where  $W_{ij}$  represents the weight of the influence of jellyfish  $i$  on the information from jellyfish  $j$ :

$$W_{ij} = (f(X_j) / \sum_k f(X_k)) * \exp(-\text{Distance}(X_i, X_j)/\sigma) * \theta_{ij}$$

Where  $\sigma$  is the influence attenuation coefficient,  $\theta_{ij} = 1$  when  $j \in \text{neighbors}_i$ , and  $\theta_{ij} = 0$  otherwise.

Based on information flow, the individual position update increment is:

$$\Delta X_{i\_info} = \sum_j W_{ij} * (X_j - X_i)$$

The final position update formula, combining the pulse propulsion and information flow mechanisms, is:

$$X_{i(t+1)} = X_i(t) + F_{pulse\_i}(t) + \Delta X_{i\_info}$$

This mechanism ensures that information from high-fitness jellyfish in the population effectively guides other individuals while preventing excessive concentration that could lead to premature convergence.

#### V. Light-sensing Floating Mechanism

Some jellyfish have light-sensing capabilities, using their photoreceptors to detect the direction of light intensity for directional floating. We use the gradient of the objective function to simulate light-sensing floating behavior, guiding jellyfish toward potential optimal solutions. Let the light-sensing float vector be  $F_{light\_i}$ , and the update formula is:

$$F_{light\_i} = \gamma * (\nabla f(X_i) / \|\nabla f(X_i)\|) * L_{max} * \exp(-f(X_i)/f_{max})$$

Where  $\nabla f(X_i)$  is the objective function gradient (which can be numerically approximated);  $L_{max}$  is the maximum float step size; and  $\gamma$  is the float scaling coefficient.

Combining the previous two mechanisms, the jellyfish position update formula is:

$$X_i(t+1) = X_i(t) + F_{\text{pulse}_i}(t) + \Delta X_{\text{info}_i} + F_{\text{light}_i}$$

The light-sensing float mechanism enhances global search capabilities, enabling low-fitness jellyfish to drift along the gradient toward potential optimal solutions.

## VI. Swarm Self-Organizing Floating Mechanism

Jellyfish swarms in nature form hierarchical distributions based on density. This paper introduces a swarm self-organizing floating mechanism to maintain swarm diversity through exclusion. Assuming the population density level is  $\rho$ , the formula for the repulsion increment is:

$$\Delta X_{\text{rep}_i} = \eta * \sum_j ((X_i - X_j) / (\text{Distance}(X_i, X_j)^p + \epsilon)) * \phi(\rho_i, \rho_j)$$

Where  $p > 1$  is the repulsion exponent,  $\epsilon$  is a small constant to prevent division by zero;  $\phi(\rho_i, \rho_j) = 1$  when  $\rho_i = \rho_j$ , otherwise  $\phi(\rho_i, \rho_j) = 0$ .

The final comprehensive update formula is:

$$\begin{aligned} X_i(t+1) = & X_i(t) \\ & + \alpha * E_i(t) * (X_{\text{best}} - X_i(t)) / \text{Distance}(X_{\text{best}}, X_i(t)) \\ & + \sum_j W_{ij} * (X_j - X_i) \\ & + \gamma * (\nabla f(X_i) / \|\nabla f(X_i)\|) * L_{\text{max}} * \exp(-f(X_i)/f_{\text{max}}) \\ & + \eta * \sum_j ((X_i - X_j) / (\text{Distance}(X_i, X_j)^p + \epsilon)) * \phi(\rho_i, \rho_j) \end{aligned}$$

This formula fully simulates the jellyfish's pulsating propulsion, tentacle information perception, light-sensing buoyancy, and swarm self-organized buoyancy.

## VII. Algorithm Flow

The pseudocode for the jellyfish self-organizing pulsation optimization algorithm is as follows:

```
Initialize a swarm of jellyfish  $X_i$ , where  $i=1..N$ 
Calculate fitness  $f(X_i)$ 
 $X_{\text{best}}$  = global optimal position
Initialize swarm hierarchy  $\rho_i$ 
```

Repeat until the maximum number of iterations:

```
For each jellyfish  $X_i$ :
  Update pulsation energy  $E_i(t)$ 
  Calculate pulsation propulsion  $\Delta X_{\text{pulse}}$ 
  Calculate information flow  $\Delta X_{\text{info}}$ 
  Calculate light-sensing levitation  $\Delta X_{\text{light}}$ 
```

Calculate swarm repulsion  $\Delta X_{rep}$   
 Update position:  
 $X_i = X_i + \Delta X_{pulse} + \Delta X_{info} + \Delta X_{light} + \Delta X_{rep}$   
 Correct  $X_i$  to the search space boundary  
 Update  $X_{best}$   
 Dynamically adjust parameters  $\alpha, \gamma, \eta$   
 Return  $X_{best}$

### VIII. Algorithm Features and Theoretical Analysis

Completely biologically driven mechanism: Each formula corresponds to the actual biological behavior of jellyfish.

Breakthrough Innovative Mechanisms: Introducing pulsating energy control, asymmetric information flow, light-sensing levitation, and multi-level self-organizing levitation, achieving non-shell-like improvements.

Balancing global search and local exploitation: Low-fitness jellyfish float for energy savings, while high-fitness jellyfish provide powerful propulsion. Simultaneously, information flow guides the swarm toward optimal solutions.

Multimodal Search Capability: The swarm self-organizing levitation mechanism maintains diversity, making it suitable for complex multimodal optimization problems.

Strong Mathematical Interpretability: The formulas clearly describe each behavior, enabling convergence and dynamic behavior analysis.

### IX. Conclusion

The proposed Jellyfish Self-Organizing Pulsating Optimization Algorithm (JSOPO) is based on the biological behavioral characteristics of jellyfish and constructs mathematical models for four core mechanisms: pulsating propulsion, tentacle-sensing information flow, light-sensing levitation, and swarm self-organizing levitation. Using plain-text mathematical formulas, the algorithm update process and mechanism logic are fully described, achieving a high-level integration of biological characteristics and optimization strategies. Requiring no experimental data for validation, the JSOPO algorithm focuses on mechanism innovation and mathematical modeling. It possesses theoretical innovation and academic value, providing a theoretical foundation for further research in nature-inspired optimization algorithms.

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