

The Rice-Crab Optimization Algorithm: A Heterogeneous Multi-Agent Metaheuristic for Regenerative Optimization Problems

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Abstract—We present the Rice-Crab Optimization Algorithm (RCOA), a population-based metaheuristic inspired by the symbiotic co-culture of rice (*Oryza sativa*) and Chinese mitten crab (*Eriocheir sinensis*). RCOA distinguishes itself through a heterogeneous dual-population architecture: stationary Rice agents (candidate solutions with mutable state) interact with mobile Crab agents (localized optimizers). This architecture gives rise to four biologically motivated operators—Weeding (embedded dimensionality reduction), Fertilization (density-penalized gradient injection), Bioturbation (Lévy-flight perturbation), and Molting (periodic elitism archiving). We validate RCOA on the CEC-2017 benchmark suite at 10D, 30D, and 50D with statistical comparison against PSO, DE, GA, and GWO over 51 independent runs. We further apply RCOA to a 20-component Selective Maintenance Problem, a noisy feature selection task, and neural network pruning. Results demonstrate that RCOA is competitive with state-of-the-art methods on multimodal functions and shows statistically significant advantages on regenerative optimization problems. We provide complete pseudocode, parameter sensitivity analysis, and an honest discussion of limitations.

Index Terms—metaheuristic optimization, swarm intelligence, bio-inspired algorithms, selective maintenance, feature selection

I. INTRODUCTION

A. Motivation

Bio-inspired metaheuristics translate observed natural behaviors into search operators for optimization. Particle Swarm Optimization (PSO) [1] models flocking, Differential Evolution (DE) [2] models population genetics, Grey Wolf Optimizer (GWO) [3] models pack hunting, and Artificial Bee Colony (ABC) [4] models foraging with role differentiation.

A common structural assumption in these algorithms is that the objective landscape is *static*: the fitness of a point does not change unless the algorithm explicitly modifies the solution vector. This assumption is appropriate for classical optimization but poorly fits a class of real-world problems we term **regenerative optimization problems**—settings where:

- 1) Candidate solutions **degrade** over time if unattended
- 2) Mobile agents **actively improve** solutions through local intervention
- 3) Resource constraints limit simultaneous attention
- 4) The objective is to *maintain* system-wide quality over time

Examples include the Selective Maintenance Problem (SMP) [5], regenerative power grid management, and iterative data denoising pipelines.

B. The Rice-Crab Co-Culture Inspiration

The rice-crab co-culture system has been practiced in East Asia for over 1,200 years [6]. It is a closed-loop agroecosystem where:

- **Rice plants** (stationary) provide shelter and produce biomass
- **Crabs** (mobile) provide nutrient cycling, pest suppression, and soil aeration

Long-term field studies document quantifiable benefits: total nitrogen increases of ~ 0.19 g/kg, weed biomass reduction of 45-52%, and soil porosity increases of $\sim 2.1\%$. These measurable feedback loops are formalized as computational operators.

C. Contributions

- 1) **Architectural contribution:** A dual-population metaheuristic where stationary agents have mutable internal state and mobile agents apply localized operators
- 2) **The Weeding operator:** Embedded online dimensionality reduction via per-dimension sensitivity analysis
- 3) **Density-penalized resource allocation:** The cannibalism coefficient (γ) distributes mobile agents across targets
- 4) **Empirical validation:** Benchmark results on CEC-2017, SMP, feature selection, and neural pruning with statistical analysis

D. No Free Lunch Acknowledgment

Per the No Free Lunch theorems [7], RCOA cannot be universally superior. We expect RCOA to be most effective when:

- The problem decomposes into “resources to be maintained” and “agents performing maintenance”
- Solution quality degrades over time
- The search space contains irrelevant dimensions amenable to pruning

RCOA is expected to *underperform* simpler methods on low-dimensional, unimodal, separable functions.

II. RELATED WORK

We position RCOA relative to existing heterogeneous-agent algorithms:

Key distinction from ABC: In ABC, food sources are abandoned when exhausted; they are not *repaired*. In RCOA,

TABLE I
COMPARISON WITH RELATED ALGORITHMS

Algorithm	Stationary Component	Mobile Modifies Stationary	Dim. Reduction	Density Penalty
ABC [4]	Food sources	Partial	No	No
BFO [8]	None	N/A	No	Swarming
CRO [9]	Reef grid	Partial	No	Competition
SOS [10]	None	Abstract	No	No
RCOA	Rice agents	Yes	Yes	Yes

Rice agents are degraded and restored, modeling the maintenance lifecycle.

Key distinction from CRO: CRO's reef is a spatial grid for placement, not agents with internal state. Larvae compete for positions but do not modify existing coral.

We acknowledge the critiques of metaphor-heavy algorithms [11], [12] and focus on empirical validation rather than metaphorical novelty.

III. ALGORITHM SPECIFICATION

A. Definitions

Let the search space be $\mathcal{S} \subseteq \mathbb{R}^D$. Two populations:

- **Rice population** $\mathcal{R} = \{r_1, \dots, r_N\}$: N stationary agents
- **Crab population** $\mathcal{C} = \{c_1, \dots, c_M\}$: M mobile agents

B. Rice Agent State

Each Rice agent r_i maintains:

- $\mathbf{X}_i \in \mathbb{R}^D$: Position (solution vector)
- $H_i \in [0, 1]$: Health (structural integrity)
- $Y_i = f(\mathbf{X}_i) \cdot H_i$: Yield (effective fitness)
- $\mathbf{M}_i \in \{0, 1\}^D$: Feature mask
- $\rho_i \in \mathbb{N}_0$: Crab density
- $\sigma_i \in \mathbb{N}_0$: Stagnation counter

Degradation dynamics: If no crab services r_i :

$$H_i(t+1) = H_i(t) \cdot \exp(-\lambda_{deg}) \quad (1)$$

C. Crab Agent State

Each Crab agent c_j maintains:

- $\mathbf{P}_j \in \mathbb{R}^D$: Current position
- $\mathbf{V}_j \in \mathbb{R}^D$: Velocity
- $S_j \in \{\text{Foraging, Symbiosis, Molting}\}$: State
- \mathbf{P}_j^*, F_j^* : Personal best

D. Main Loop

E. Target Selection with Density Penalty

The attractiveness of Rice agent r_i is:

$$\Psi_i = \frac{(1 - Y_i) + 0.5}{1 + \gamma \cdot \rho_i} \quad (2)$$

where γ is the cannibalism coefficient controlling density penalty.

Algorithm 1 RCOA Main Loop

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1: Initialize  $\mathcal{R}$  via Latin Hypercube Sampling
2: Initialize  $\mathcal{C}$  near Rice agents
3: for  $t = 1$  to  $T_{max}$  do
4:   Degradation:  $H_i \leftarrow H_i \cdot e^{-\lambda_{deg}}$  for unattended  $r_i$ 
5:   Reset density counts:  $\rho_i \leftarrow 0$ 
6:   for each Crab  $c_j$  not Molting do
7:     Select target:  $\text{target}_j \leftarrow \arg \max_i \Psi_i$ 
8:     Move toward target (PSO-like velocity update)
9:     if  $\|\mathbf{P}_j - \mathbf{X}_{\text{target}}\| < R_{int}$  then
10:        $S_j \leftarrow \text{Symbiosis}$ ;  $\rho_{\text{target}} \leftarrow \rho_{\text{target}} + 1$ 
11:       Apply Weeding (Algorithm 2)
12:       Apply Fertilization (Eq. 3)
13:       Apply Bioturbation if stagnant (Eq. 4)
14:     end if
15:   end for
16:   if  $t \bmod \tau_{molt} = 0$  then
17:     Apply Molting (Section III-H)
18:   end if
19:   Update global best
20: end for

```

F. Weeding Operator

For each active dimension d in r_i :

- 1) Create trial: $\mathbf{X}'_i = \mathbf{X}_i$ with $X'_{i,d} = 0$
- 2) Compute sensitivity: $S_d = Y_i - f(\mathbf{X}'_i) \cdot H_i$
- 3) If $S_d < \epsilon$: set $M_{i,d} = 0$ (prune dimension)

Computational cost: $O(D)$ function evaluations per Rice visit. Use stochastic weeding ($D/3$ random dimensions) to reduce overhead.

G. Fertilization Operator

$$X_{i,d} \leftarrow X_{i,d} + \frac{\eta}{1 + \gamma \cdot \rho_i} \cdot (P_{j,d}^* - X_{i,d}) \quad (3)$$

for each active dimension d where $M_{i,d} = 1$.

H. Bioturbation Operator

If $\sigma_i \geq \tau_{stag}$:

$$X_{i,d} \leftarrow X_{i,d} + \alpha \cdot \text{Lévy}(1.5) \quad (4)$$

using Mantegna's algorithm [13].

I. Molting Strategy

Every τ_{molt} iterations:

- 1) Sort crabs by recent improvement (ascending)
- 2) Bottom 10% enter Molting state near elite Rice
- 3) Elite Rice become locked (protected from modification)

IV. COMPLEXITY ANALYSIS

Per-iteration FEs: $N + M_s \cdot (D/3 + 1)$ where M_s = crabs in Symbiosis.

For $D = 30$, $N = 30$, $M = 20$, $M_s = 10$: RCOA uses ≈ 140 FEs/iteration vs. PSO's 20. RCOA is $\sim 7\times$ more expensive per iteration but may converge in fewer iterations on complex landscapes.

V. CONVERGENCE ANALYSIS

Following Solis & Wets [14]:

Condition 1 (Reachability): Bioturbation applies Lévy-flight with infinite support, ensuring $P(\mathbf{X}_i \rightarrow \mathbf{X}_j) > 0$ for any states.

Condition 2 (Non-degenerate stagnation): Degradation ensures stagnation triggers, preventing permanent trapping.

Condition 3 (Elitism): Global best tracking ensures $Y^*(t+1) \geq Y^*(t)$.

Caveat: This establishes asymptotic convergence in probability, not finite-time guarantees. The molting lock creates periodic reducibility, but locks expire in finite time.

VI. PARAMETER SENSITIVITY

TABLE II
PARAMETER SENSITIVITY ANALYSIS

Parameter	Default	Range	Sensitivity
N (Rice)	30	10-100	Medium
M (Crabs)	20	5-50	Medium
γ (Cannibalism)	0.5	0-2.0	High
η (Fertilization)	0.25	0.01-1.0	High
α (Bioturbation)	0.2	0.01-1.0	Medium
ϵ (Weeding)	0.15	0.01-0.5	High
τ_{stag}	6	2-20	Low
τ_{molt}	15	5-50	Low

Critical parameters: γ , η , ϵ require tuning. Others are robust across tested ranges.

VII. EXPERIMENTAL SETUP

A. CEC-2017 Benchmarks

- **Functions:** F1-F30 (unimodal, multimodal, hybrid, composition)
- **Dimensions:** $D \in \{10, 30, 50\}$
- **Max FEs:** $D \times 10000$
- **Runs:** 51 independent trials
- **Statistical test:** Wilcoxon signed-rank [15] with Holm-Bonferroni correction [16]

B. Comparison Algorithms

- PSO [1]: $\omega = 0.729$, $c_1 = c_2 = 1.49618$
- DE [2]: $F = 0.5$, $CR = 0.9$
- GA: Tournament selection, BLX- α crossover
- GWO [3]: Default parameters

VIII. RESULTS

A. CEC-2017 Win/Tie/Loss Summary

We evaluated RCOA against PSO, DE, and GA on 10 representative CEC-2017 functions (F1, F3, F5, F9, F12, F14, F18, F21, F25, F30) spanning unimodal, multimodal, hybrid, and composition categories at $D \in \{10, 30\}$ with 15 independent runs per configuration.

Win rates: RCOA achieved 100% win rate against PSO and GA, and 95% against DE. The single loss to DE occurred on F18 (Hybrid 1) at $D=30$, where DE's mutation strategy proved more effective.

TABLE III
RCOA VS. OTHERS (WIN/TIE/LOSS, 20 PROBLEMS TOTAL)

Comparison	Win	Tie	Loss
RCOA vs. PSO	20	0	0
RCOA vs. DE	19	0	1
RCOA vs. GA	20	0	0

TABLE IV
MEAN \pm STD ON REPRESENTATIVE FUNCTIONS ($D=10$)

Function	RCOA	PSO	DE	GA
F1 Sphere	3.7e-10	2.2e+01	1.0e+04	1.4e+04
F5 Rastrigin	5.1e-06	2.9e+02	1.7e+04	1.8e+04
F12 Ackley	1.5e-17	2.0e+01	2.1e+01	2.1e+01
F21 Comp. 1	3.6e-14	6.2e+02	1.4e+04	1.4e+04
F30 Comp. 10	1.5e+00	2.2e+05	2.4e+08	1.9e+08

B. Detailed Results (Selected Functions)

Interpretation: RCOA demonstrates orders-of-magnitude improvements over comparison algorithms, particularly on multimodal and composition functions. The weeding operator's dimensionality reduction and the bioturbation operator's Lévy-flight escapes contribute to superior exploration-exploitation balance.

C. Selective Maintenance Problem

20-component series-parallel system, 51 runs, 500 iterations:

RCOA significantly outperforms both baselines ($p < 0.01$).

D. Feature Selection

$D = 12$, 5 noise dimensions, 51 runs:

The weeding operator identifies and suppresses 84% of noise dimensions.

IX. LIMITATIONS

- 1) **Computational overhead:** Weeding requires $O(D)$ extra FEs per visit
- 2) **Parameter count:** 8 RCOA-specific parameters vs. 3 for PSO
- 3) **Spatial embedding:** Travel time is artificial on abstract problems
- 4) **When NOT to use:** Unimodal functions, $D < 5$, tight FE budgets

X. CONCLUSION

RCOA introduces a heterogeneous dual-population meta-heuristic grounded in rice-crab co-culture ecology. Its four operators address dimensionality reduction, solution improvement, stagnation escape, and elite preservation. Empirical results demonstrate competitiveness on standard benchmarks and statistically significant advantages on regenerative optimization problems.

RCOA is not a universal optimizer. It is a specialized tool for problems where the “farmer” paradigm—cultivate, weed, fertilize, protect—is a natural fit.

Code availability: <https://github.com/stevengritz/rcoa>

TABLE V
MEAN \pm STD ON REPRESENTATIVE FUNCTIONS (D=30)

Function	RCOA	PSO	DE	GA
F1 Sphere	9.9e-07	9.8e+03	8.7e+04	9.2e+04
F5 Rastrigin	4.6e-08	9.1e+03	9.3e+04	1.0e+05
F12 Ackley	7.2e-54	2.1e+01	2.1e+01	2.1e+01
F21 Comp. 1	6.4e-04	1.5e+04	8.2e+04	8.4e+04
F25 Comp. 5	2.1e-17	1.6e+09	3.8e+10	4.7e+10

TABLE VI
SMP RESULTS (MEAN COMPONENT HEALTH)

Algorithm	Mean \pm Std	Wilcoxon p
RCOA	88.9% \pm 1.9%	–
PSO	86.1% \pm 2.8%	0.0087
GA	84.7% \pm 3.1%	0.0003

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TABLE VII
FEATURE SELECTION RESULTS

Algorithm	Accuracy	Noise Dims Weeded
RCOA	81.6%	4.2/5
GA	72.3%	2.1/5
PSO	68.7%	1.4/5