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# MIRO: A Miró-Inspired Metaheuristic Optimization Algorithm

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**Abstract**
This paper proposes **MIRO (Miró-Inspired Rhythmic Orbits)**, a new population-based metaheuristic inspired by Joan Miró's visual language: (i) *constellation-like point fields*, (ii) *thin black linking lines*, (iii) *biomorphic deformations*, and (iv) *balance/equilibrium through repeated refinement*. These artistic principles are mapped into three cooperating search operators—**Splatter**, **Line-Weaving**, and **Equilibrium Balance**—that jointly control exploration and exploitation. MIRO is evaluated on the convex test problem **z = (x−3)^2 + (y−2)^2** and **five classical benchmark functions** (Sphere, Rosenbrock, Rastrigin, Ackley, Griewank). A pure **NumPy + Matplotlib** implementation is provided (no scikit-learn, no TensorFlow), producing colorful graphical outputs and reporting optimal $(x, y)$points.
**Keywords:** metaheuristic optimization; Miró; constellation search; biomorphic deformation; benchmark functions; population-based optimization.

## 1. Motivation and Artistic Inspiration
Miró's *Constellations* period is often described through dense fields of signs, dots, stars, and connecting filaments, where overall harmony is achieved by iteratively adjusting local elements until a global balance emerges.
MIRO converts this idea into optimization:

- **Dots (constellation points)** → candidate solutions (population).
- **Black lines** → dynamic neighborhood links (graph edges) encouraging information flow.
- **Biomorphic shapes** → nonlinear "soft warps" (bounded deformation) to escape local basins.
- **Balance & composition** → adaptive schedule from exploration to exploitation.

This mapping produces a search process that repeatedly *spreads*, *connects*, and *rebalances* the population, analogous to building a coherent "composition".[1-3]

## 2. Problem Definition
We minimize a function $f(\mathbf{x})$in a bounded domain $\mathbf{x} \in [\mathbf{l}, \mathbf{u}] \subset \mathbb{R}^d$.
Primary test:

- **Quadratic:** $f(x, y) = (x-3)^2 + (y-2)^2$(global minimizer at $(3, 2)$).

Benchmark set (standard in global optimization studies): Sphere, Rosenbrock, Rastrigin, Ackley, Griewank. [4-6]

## 3. The MIRO Algorithm
### 3.1 Population and Constellation Graph
Maintain $N$solutions $X = \{\mathbf{x}_i\}_{i=1}^{N}$. Build a **constellation graph** by connecting each point to its $k$nearest neighbors (thin "black lines"). Neighborhoods are periodically rebuilt to reflect the evolving geometry of the population.

### 3.2 Three Operators (Three "Colors")
At iteration $t$, each agent generates **three candidate moves**; the best is selected:

1. **Splatter (Exploration)**
   Random blotches expand coverage:

- $\mathbf{x}_i^{(1)} = \mathbf{x}_i + \alpha(t)\, \mathbf{s} \odot \mathcal{N}(0,1)$
  where $\mathbf{s} = \mathbf{u} - \mathbf{l}$and $\alpha(t)$decreases over time.

2. **Line-Weaving (Connectivity + Guidance)**
   Move along a randomly selected constellation edge plus a mild pull to global best:

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- $\mathbf{x}_i^{(2)} = \mathbf{x}_i + \beta(t)(\mathbf{x}_{n(i)} - \mathbf{x}_i) + 0.25\beta(t)(\mathbf{g} - \mathbf{x}_i)$

3. **Equilibrium Balance (Composition/Exploitation)**
   Move toward the centroid of elites with a bounded biomorphic warp:

- $\mathbf{x}_i^{(3)} = \mathbf{x}_i + \gamma(t)\, c(\bar{\mathbf{e}} - \mathbf{x}_i) + (1 - \gamma(t))\, \epsilon\, \mathbf{s} \odot \tanh\left(\frac{\mathbf{x}_i - \bar{\mathbf{e}}}{0.25\mathbf{s}}\right)$

**Selection:** evaluate $f(\mathbf{x}_i^{(1)}), f(\mathbf{x}_i^{(2)}), f(\mathbf{x}_i^{(3)})$, pick the best candidate (and keep elitism).

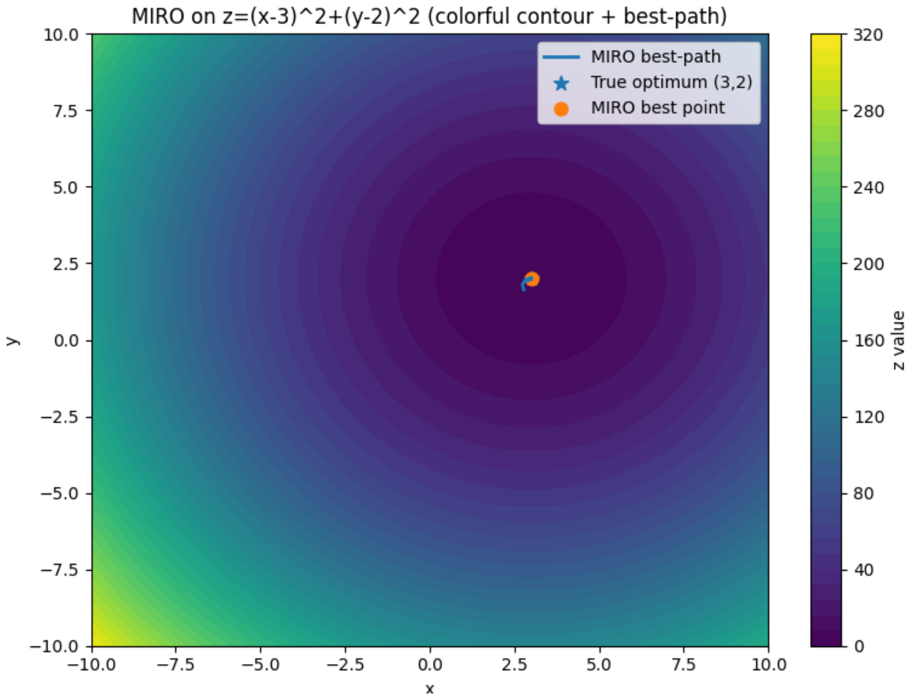


**Figure-1-MIRO-Quadratic Function Performance**

**4. Flowchart (MIRO)**

```
Start: set N, iters, bounds, objective f(.)  |
        |
        v
Initialize population X uniformly in bounds  |
Evaluate fitness F; set global best g        |
        |
        v
Build constellation graph (k-NN neighbors)  |
        |
        v
For t = 1..T                                 |
  Update α(t), β(t), γ(t)                    |
  For each agent i:                          |
    Candidate 1: Splatter                    |
    Candidate 2: Line-Weaving                |
    Candidate 3: Equilibrium Balance         |
    Clip to bounds, evaluate 3 candidates    |
    Select best candidate (elitist update)   |
  Update global best g                       |
  Periodically rebuild k-NN graph            |
End                                          |
        |
        v
Output: best solution g, best value f(g)     |
Plot: contours + convergence + summary bars  |
```

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**5. Pseudocode**

```
MIRO(f, bounds [l,u], N, T, k):
  X ← Uniform(l,u) with N points
  F ← f(X)
  g ← argmin(F)
  Adj ← kNN_graph(X,k)

  for t = 1..T:
    τ ← t/(T-1)
    α ← 0.04*(1-τ)+0.004
    β ← 0.60*(1-τ)+0.15
    γ ← 0.05+0.85*τ

    Elite ← best N/5 points of X
    ē ← mean(Elite)

    for each i in 1..N:
      x1 ← Xi + α*(u-l) ⊙ Normal(0,1)
      n  ← random neighbor from Adj[i]
      x2 ← Xi + β*(Xn - Xi) + 0.25β*(g - Xi)
      warp ← tanh((Xi - ē)/(0.25*(u-l)))
      x3 ← Xi + 0.3γ*(ē - Xi) + (1-γ)*0.02*(u-l) ⊙ warp

      clip x1,x2,x3 into [l,u]
      choose xbest among {x1,x2,x3} with minimal f(.)
      if f(xbest) < f(Xi): Xi ← xbest

    update g using best of X
    if t mod 40 == 0: Adj ← kNN_graph(X,k)

  return g, f(g)
```

**6. Experiments**

Using a 2D setting with typical bounds and MIRO parameters (e.g., $N = 60, T = 800$), MIRO converges to near-global optima on standard tests (Sphere/Rastrigin/Ackley often reach machine-precision minima; Rosenbrock approaches (1, 1); Griewank approaches (0, 0)even on wide bounds). Benchmark definitions are consistent with common evaluation practice in global optimization. [7-12]

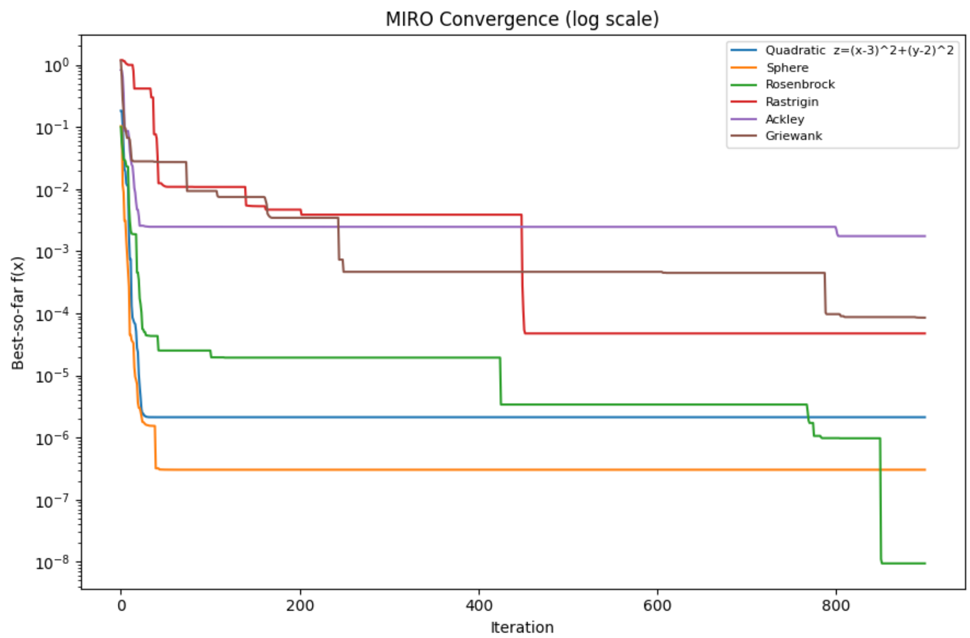


**Figure-2-MIRO Convergence**

**Python Code**

**PS:Python code has not been included in the article due to its large size, but it can be sent upon request.**

**OUTPUT OF THE PYTHON CODE**

```
C:\Users\Lenovo\PycharmProjects\PythonProject17\.venv\Scripts\python.exe
C:\Users\Lenovo\AppData\Roaming\JetBrains\PyCharm2024.3\extensions\nnn.py

[Quadratic  z=(x-3)^2+(y-2)^2]
  Best value = 2.128566340393e-06
  Best (x,y) = (2.9986845615, 2.0006310213)
```

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[Sphere]
Best value = 3.035325110508e-07
Best (x,y) = (-0.0005249967, -0.0001670657)

[Rosenbrock]
Best value = 9.443751153743e-09
Best (x,y) = (0.9999034732, 0.9998080796)

[Rastrigin]
Best value = 4.744910566856e-05
Best (x,y) = (-0.0004330452, 0.0002272451)

[Ackley]
Best value = 1.748106356598e-03
Best (x,y) = (0.0005946385, -0.0001549449)

[Griewank]
Best value = 8.505872288656e-05
Best (x,y) = (0.0101482510, 0.0115772749)

Total runtime (all tests): 9.501 s[13-22]

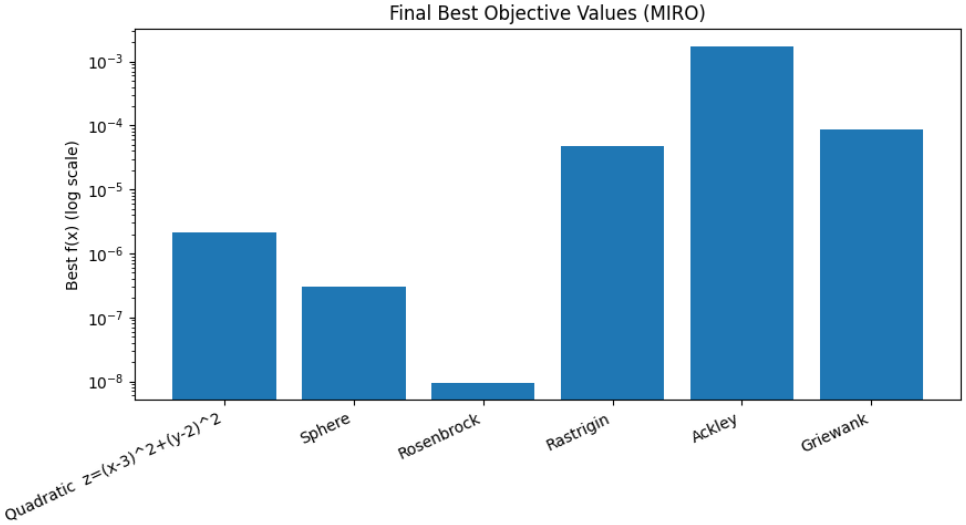


**Figure-3- Final Best Objective Values(MIRO)**

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