Exploration Enhanced Particle Swarm Optimization using Guided Re-Initialization

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Introduction

- Multidimensional problems highly complex
  - Conventional computational algorithms not suitable
- PSO may be used
  - computationally cheaper and more robust
  - Single version of PSO covers many applications

Particle Swarm Optimization

- Swarm intelligence
  - Based on collective nature of unsophisticated entities/agents
- Multidimensional space represents solutions
- Movement governed by factors
  - Social
    - specific to the swarm as a whole
  - Cognitive
    - specific to the individual

Particle Swarm Optimization

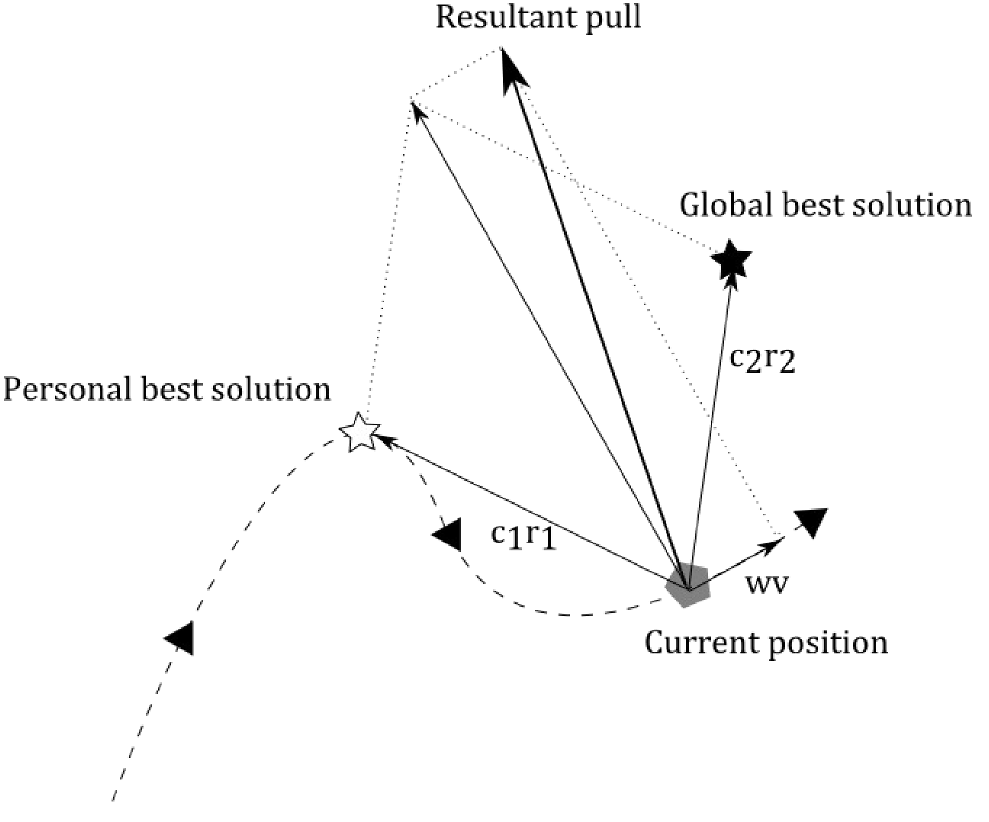
- Algorithm
  - *Boid* described by position and velocity
  - Maintain individual *personal best*
  - Sharing of information gives rise to *global best*

  - Velocity and position for *boid* [i] updated as

$$\boldsymbol{v_i = wv_i + c_1r_1(p_i - x_i) + c_2r_2\,(g - x_i)}$$

$$\boldsymbol{x_i = x_i + v_i}$$

- Velocity calculation for a particle in PSO



Particle Swarm Optimization

- Limitations
  - Extensive information flow
    - Premature convergence
    - Suboptimal solution
  - Redundant calculations when converging
    - We know that particles are converging

Particle Swarm Optimization

- Some PSO Variants
  - Re-initialization or disturbance to particles
    - Adaptive PSO, Heuristic PSO, Perturbation PSO
  - Radius
    - Species in a Particle Swarm Optimizer (SPSO)
  - Some other variants
    - Comprehensive learning PSO, Dynamic Multi-Swarm PSO and Fully Informed Particle Swarm

The Proposed Approach

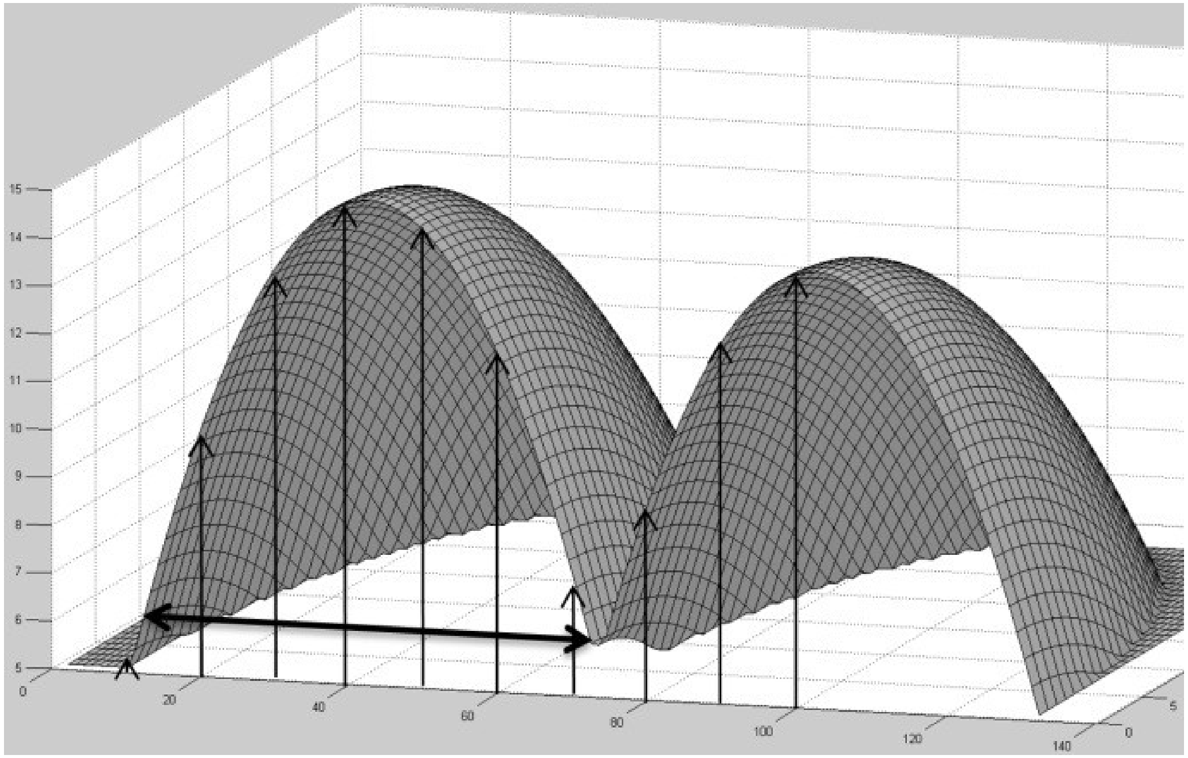
- Inspired by the concept of teleportation
- Region (*portal*) located around global best
  - Variable *Radius of Effect* (*RoE*)

The Proposed Approach

- Algorithm
  - Particles may stay outside/inside *RoE*
    - Exploration vs convergence
  - Particles outside *RoE*
    - Particles approaching *gbest* enter *RoE*
    - Position and velocity reinitialized to outside location
    - *RoE* increased (limited to maximum)
  - Particles inside *RoE*
    - Particles trajectory might go out of *RoE*
    - Position and velocity reinitialized to inside location
    - *RoE* decreased

The Proposed Approach

- *RoE* limit



The Proposed Approach

- Algorithm
  - Particles initially stay outside *RoE*
    - Exploration boost
  - Individual particles converted to stay inside *RoE*
    - Over time
    - Convergence boost

The Proposed Approach

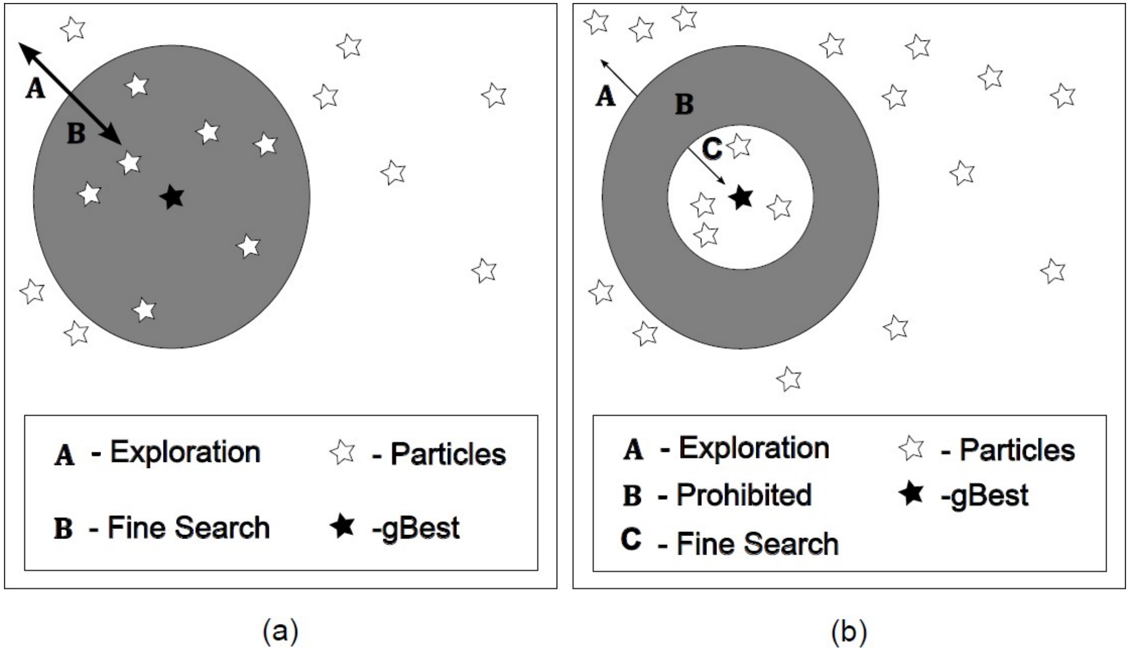
- Single Portal Model
  - One portal around *gbest*
  - Portal is like hollow hypersphere
    - No thickness
  - *RoE* initially increases then decreases

The Proposed Approach

- Two Portal Model
  - Outer and inner portals
    - Different portals dedicated to exploration and convergence
  - Outer *RoE* only increases
  - Inner *RoE* only decreases
  - Region between two portals is empty

The Proposed Approach

- Single portal and two portal model



The Proposed Approach

Single Portal Model	**Two Portal Model**
Conflict for *RoE* manipulation between exploration and conversion particle groups if single portal	Separate *RoE* values for exploration and convergence. Better precision achievable
RoE reset controlled by particles outside portal	Different *RoE* values controlled by different particle groups
Particles may explore entire hyperspace. More exhaustive search	Region between two portals remained possibly unexplored

Experimental Studies

- PSO models executed several times
  - Average fitness value calculated
- Input and output parameters tuned
  - Unimodal and multimodal separately
- Fitness values compared against original PSO model

Experimental Studies

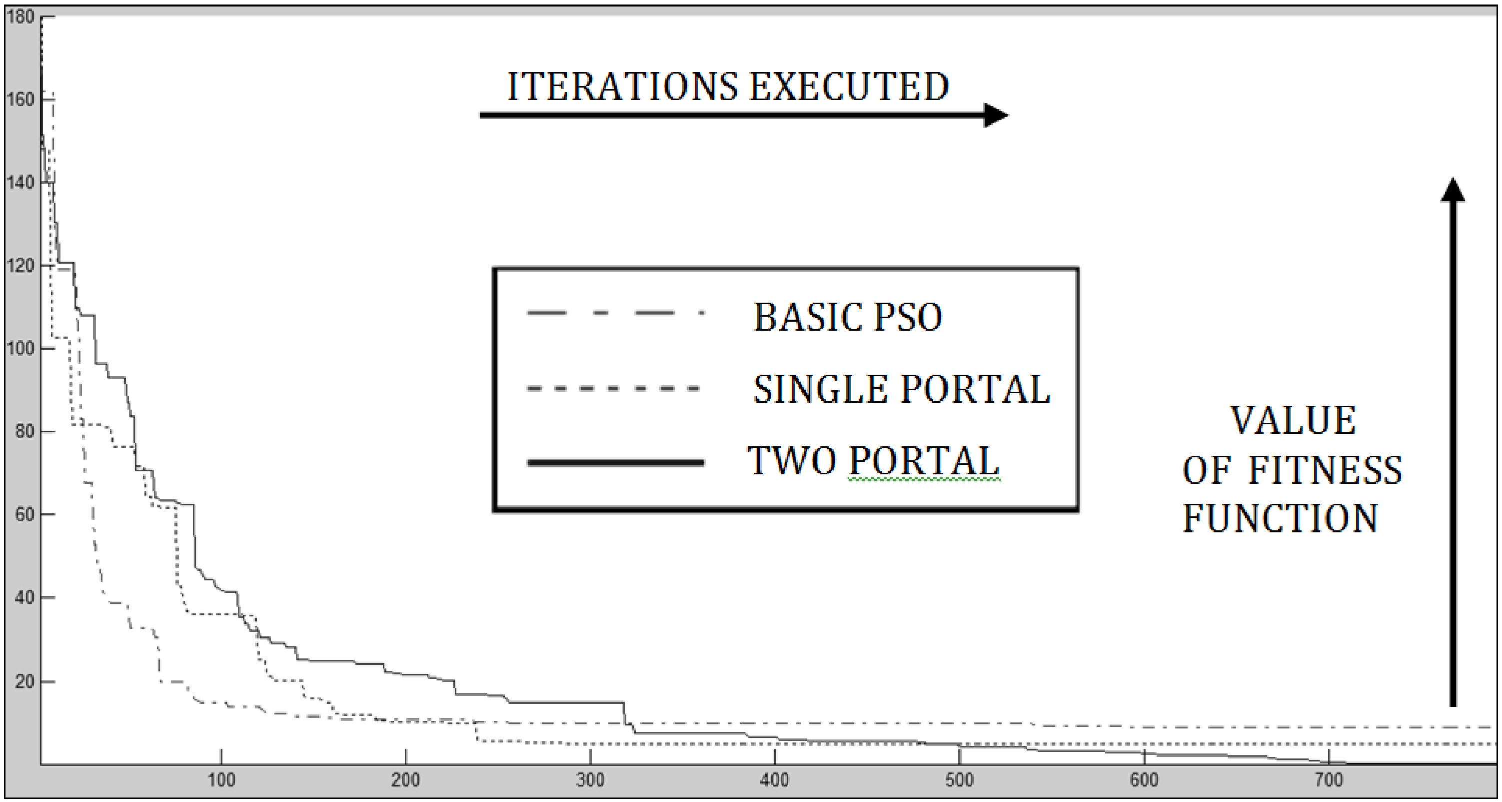
- Results
  - Best performance improvement for Rastrigin F1
    - Two portal better than single portal
  - Parameter tuning done for unimodal and multimodal
    - Collective fitness of respective functions used

Experimental Studies

Function	Original Model	Single Portal Model	Two Portal Model
DeJong	0.0000	0.0000	0.9604
Griewank	0.9995	0.9995	0.9995
Rastrigin F1	6.9647	2.9879	0.1392
Rosenbrock	146.7320	123.6780	109.0720
Schaffer F6	0.0372	0.0262	0.0235

Experimental Studies

- Fitness value for Rastrigin F1 function



Experimental Studies

- Discussion
  - Dejong
    - Deviation in fitness for two portal model
      - Due to nature of particle distribution
  - Rosenbrock
    - Premature convergence avoided by proposed models
    - Improvement in fitness value
    - Single portal suffers from RoE conflict
      - Two portal generates better fitness value

Experimental Studies

- Discussion
  - Rastrigin F1 and Schaffer F6
    - Highly multimodal
    - Original PSO converges at local optima
    - Models provide better fitness
      - Two portal better than single portal model
  - Griewank
    - Same result
      - All models have same base implementation of algorithm

Experimental Studies

- Discussion
  - Forbidden region in two portal model does not degrade results
    - Probably due to forbidden region being on “slant” of “mountain”
  - Number of tunable parameters increased
    - More difficult tuning
    - More customizable

Experimental Studies

- Future Work
  - Current *RoE* modifications time dependent
    - Make dependent on particle group population ratios
  - Current RoE modifications simple
    - Make complex
  - Particles start from staying outside portal to inside
    - Reverse process may be added where suitable
  - Comparisons with other PSO versions

Conclusion

- Original PSO model and drawbacks discussed
- Two implementation of variant proposed
- Proposed model good for multimodal functions
  - Able to avoid premature convergence

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