PSO Variants and Specializations

Paper: Particle Swarm Optimization
An Overview
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PSO Variants

- Binary Particle Swarms
- Dynamic Problems
- Noisy Functions
- Hybrids and adaptive particle swarms
- PSOs with Diversity Control
- Bare-bones PSO
Binary Particle Swarm

- Kennedy and Eberhart (1997)
  - Operating on bit Strings
  - Determine bits by threshold $s(x_{id})$
    \[ s(x_{id}) = \frac{1}{1 + \exp(-x_{id})} \]
  - If random number $r < s(x_{id})$, then 1 otherwise 0

- Kennedy and Spears (1998)
  - Compared binary PSO with several Gas
  - Used Spears’ multimodal random problem generator
    - No of local optima, dimension etc.
  - Bin PSO was the only winner in all cases!
  - Worked faster than all except the very simplest ones.
Dynamic Problems

• Fitness function changes over time
  – Always challenging for PSO

• Parsopoulos and Vrahatis (2001)
  – PSO can track slowly moving optima with no change

• Carlisle and Dozier (2000-01)
  – Dynamic problems two phases
    • Detect change
      – By a different function value upon re-evaluation
    • Respond
      – The current position was set to the previous best
      – (More successful) Previous bests are compared with current positions
Dynamic problem cont..

• Parsopoulos and Vrahatis (2004)
  – Maintain a level of diversity throughout the run
  – Repulsion keeps the particles away from the detected optima

• Blackwell and Bentley (2002)
  – Introduced charged particles into the swarm
  – Particles repel and orbit a converging nucleus of ‘neutral’ particles
  – Charged particles detect optimum shift with their orbit

• Dynamic multimodal landscapes are the most challenging for PSO
Noisy Functions

• Noisy fitness function often found in real-world problems
  – Fitness Function remains the same
  – But the evaluation is noisy
  – If a PSO explores the same position more than once, the fitness values may differ

• Parsopoulos and Vrahatis (2001)
  – Added a Gaussian distributed random noise to the fitness function
  – And Random rotation of the search space
  – PSO is still effective with noise and some cases noise even helped to avoid local optima!
Hybrids and Adaptive Particle Swarms

• Evolutionary strategies were borrowed
• Angeline (1998)
  – Intentionally hybridized particle swarms
  – ‘Good’ particles were reproduced with mutation
  – ‘Bad’ particles were eliminated
  – Results show that PSO is benefitted from hybridization
Hybridized Swarms cont..

• Miranda and Fonseca (2002)
  – Adding Gaussian random values
  – Perturb $\chi, \phi_1, \phi_2$ and the position of neighborhood
    best but not the individual best
  – Evolutionary self-adapting PSO shown excellent
    performance in comparison to standard PSO

• Loovbjerg et al. (2001)
  – Used ‘breeding’, borrowed from GA
  – Selected particles were paired at random
  – Positions and velocities were calculated from weighted
    arithmetic averages of selected particles
  – Results were encouraging though the model was
    reported not to be superior than standard PSO
PSO with Diversity Control

- Diverse particles were used for avoiding premature convergence on local optima
- Loovjerg (2002)
  - Used self-organized criticality to attain diversity
  - When two particles are too close to each other
    - A variable ‘critical value’ is incremented
    - If it reaches the criticality threshold
      - the particle disperses its criticality to nearby particles
      - Then it relocates itself
PSO with Diversity Control cont..

• Krink et al. (2002)
  – Diversify particles to prevent them clustering too tightly in one region
  – “Spatially extended”
    • Each particle is conceptualized to have a sphere of some radius
    • When a particle collides with another, it bounces off
Bare-bones PSO

- Kennedy (2003)
  - A velocity-free PSO
  - Move particles according to probability distribution rather than addition of velocity
  - Particle update rule was replaced with a Gaussian distribution of mean \((\vec{p}_i + \vec{p}_g)/2\) and standard deviation \(|\vec{p}_i - \vec{p}_g|\)
  - Results were good on some problems but was proved less effective in others
Applications of PSO

• Applications were divided into 26 categories
• Based on 1100 publications on IEEE Xplore
• Selected application categories
  – Image and video analysis (7.6%)
  – Design and re-structuring of electricity network (7.1%)
  – Control applications (7.0%)
  – Applications in electronics and electromagnetics (5.8%)
  – Antenna design (5.8%)
  – Power generation and power systems (5.8%)
  – Scheduling (5.6%) etc.
Open Questions

• Initialization
  – Choosing swarm size, particle positions
  – Randomly in the search space

• Termination
  – Usually acceptable error or total number of function evaluation
  – PSO can still suffer premature convergence
Open Question cont..

• Particle selection
  – Particle dynamics variants:
    • spherical particles,
    • inter-particle repulsive forces,
    • sliding (rather than flying) particles,

• Adaptation
  – The goal of PSO research is to find completely adapting, parameter-free optimizer
    • A multitude of swarms run for a given problem, each with different parameters, number of particles and informer topology
    • Or a series of sequential trials can be performed with different parameters
• Questions?