MULTIAGENTS AND DYNAMIC OPTIMIZATION PROBLEMS: SIMPLE RULES FOR IMPROVING PERFORMANCE

Antonio Masegosa, Juan R. González, Carlos Cruz, Ignacio G. del Amo, Pavel Novoa, David A. Pelta

Models of Decision and Optimization Research Group
Dept. of Computer Science and AI,
University of Granada, Spain
Outline of the talk

- Who we are
- What we have now
  - multiswarms & DOP
  - Cooperative Strategies for DOP
- What we are doing and some open questions
Who we are

- Models of Decision and Optimization Research Group (modo.ugr.es)
- 7 Phd + 3 Phd Students

Research lines
- Decision making under uncertainty
- Optimization with metaheuristics (cooperative methods)
- Adversarial Domains
- Car racing videogames 😊
- Intelligent Optimization Strategies in Uncertain and Dynamic Environments
Intelligent Optimization Strategies in Uncertain and Dynamic Environments

Current social-technological context

- Telecommunication
- Users
- Infrastructures
- Services

New Scenarios

- Uncertainty
- Dynamism

Soft Computing Techniques

- Fuzzy Sets & Systems
- Metaheuristics
Intelligent Optimization Strategies in Uncertain and Dynamic Environments

The core of my talk will be here.
Dynamic Optimization Problems

- What are we talking about?
- Let’s see some videos
Swarms and Multiswarms in DOP

- Outdated memory
- Diversity loss
- Locality after a change
- Slow response to changes in the environment

“Atomic” scheme
Charged or quantum particles

Multiple swarm
Simultaneous exploration
Exclusión, anti-convergence properties

Simple ways to improve

Adapting the types of the particles

Changing the behaviour of some swarms
The particles (quantum, trajectory) do not contribute equally to the improvements.
Rule 1: “Change Rule”

**IF** a change in the environment has occurred recently

**THEN** temporarily *increase* the number of *quantum* particles AND *decrease* the number of *trajectory* particles

The length of period between changes is estimated (and assumed constant)
Swarm Control: Efficiency improvement

What we can do with this swarm?
Rule 2: “Rand Rule”

**IF** a swarm is showing bad performance

**THEN** relocate the swarm randomly OR stop it if there is not enough time

Bad Performance means that the Swarm has

**already converged** and its **fitness is low**

- Local Information related with rate of improvement
- Global Information related with the fitnesses of all of the other swarms (the g_best)

We also have definitions using measures of diversity
Rule 2: “Rand Rule”
Rule 3: Change + Rand Rule
Illustrative Examples (I)

- Experiments with scenario 2 of MPB (100 peaks, five dimensions) and Ackley (dim = 5)
- Offline error, change frequency, change severity
- Overview on MPB
Illustrative Examples (II)

- Impact of frequency

![Graph showing the impact of change frequency]

- Average offline error is plotted against change frequency (number of evaluations between changes).

- Different lines represent different strategies: mqlso, mqlso-rule-change, mqlso-rule-rand, mqlso-rule-both.
Illustrative Examples (II)

- Impact of Severity

![Graph showing the impact of severity on average offline error]
A different approach

- Most of the methods used are population-based (PSO, EAs, . . .).
- Quite assumed that several solutions are needed to avoid local minima and to better react when the problem changes.
- *Little attention has been put on trajectory-based methods.*
- Our previous work showed that they can obtain good results (at least when coupled with a cooperation strategy).
Cooperative Strategy for DOP

- Specifically designed to deal with continuous optimization
- They know how to detect a change and inform it to the Coordinator
Coordinator Control

The threshold $\lambda$-reaction regulates rule activation.

The antecedent allows to the coordinator to determine if a solver is trapped in a local minimum or has fallen many times in a previously visited optimum.

"perform an action" will relocate the agent in a new point of the search space (they are local search-based techniques).

IF the number of last local minimum visited by agent$_i$ is bigger than $\lambda$-reaction

THEN perform an action
“Perform an action”

- **Best solution (BS):** Send the best global solution to the agent with a slight modification.
- **Approaching (AP):** Reallocate the agent in an intermediate point between the solver’s and coordinator’s best solution.
- **Reactive (R):** Send the best global solution perturbed by a certain degree.
- **Visited Region List (VRL):** Uses the VRL to reallocate the solver outside the previously visited regions.
Experiments and Illustrative results

- DOPs are defined as the composition of \( m \) functions of the same type (Cone, Ackley, Griewank or Rastrigin):
  \[
  F(x) = \min\{f_1(x), f_2(x), \ldots, f_m(x)\}
  \]
- 12 heterogeneous solvers in the cooperative strategy (12 solutions are kept along the time)
- Severity changes, number of functions
MPB (cones), 10 peaks, n=5, different severities (larger circle, higher severity)
Rastringin. Variable number of functions and severities
Convergence (an idea)
Conclusions & Future Work

- Simple ideas may lead to great improvements (stop the swarms with “bad behaviour”)
- Cooperative strategies are a promising approach
- Problem generator development
  - dynamic objective function
  - dynamic restrictions
  - uncertainty in the variables
  - uncertainty in fitness
Open questions

- self-adaptation?
- new measures of performance?
- what is an instance of the problem?
- how we can ensure reproducibility?
- how we can detect, for example, cyclic changes?
Intelligent Optimization Strategies in Uncertain and Dynamic Environments

- Recent paper

- www.dynamic-optimization.org

- Contributions welcome!
  Just a bibtex file + a set of tags for every entry
References

Simple control rules in a cooperative system for dynamic optimization problems
David Pelta, Carlos Cruz, Jose L. Verdegay

A Study on Diversity and Cooperation in a Multi-Agent Strategy for Dynamic Optimization Problems,
David Pelta, Carlos Cruz

Soft Computing and Cooperative Strategies for Optimization, Carlos Cruz and David Pelta

Using Heuristic Rules to Enhance a Multiswarm PSO for Dynamic Environments

Cooperation Rules in a Trajectory-Based Centralised Cooperative Strategy for Dynamic Optimisation Problems

An Analysis of Particle Properties on a Multi-Swarm PSO for Dynamic Optimization Problems,

Improvement Strategies for Multi-swarm PSO in Dynamic Environments
THANK YOU VERY MUCH FOR YOUR ATTENTION

David A. Pelta

http://modo.ugr.es

http://www.dynamic-optimization.org

http://decsai.ugr.es/~dpeleta