Evolutionary Computing

Chapter 8

Parameter Control

Parameter Control

- Motivation
- Parameter setting
  - Tuning
  - Control
- Examples
- Extended / refined taxonomy
- Some figures about related work

Motivation (1/2)

An EA has many strategy parameters, e.g.

- mutation operator and mutation rate
- crossover operator and crossover rate
- selection mechanism and selective pressure (e.g. tournament size)
- population size

Good parameter values facilitate good performance

Q1 How to find good parameter values ?

Motivation (2/2)

EA parameters are rigid (values constant during a run)

BUT

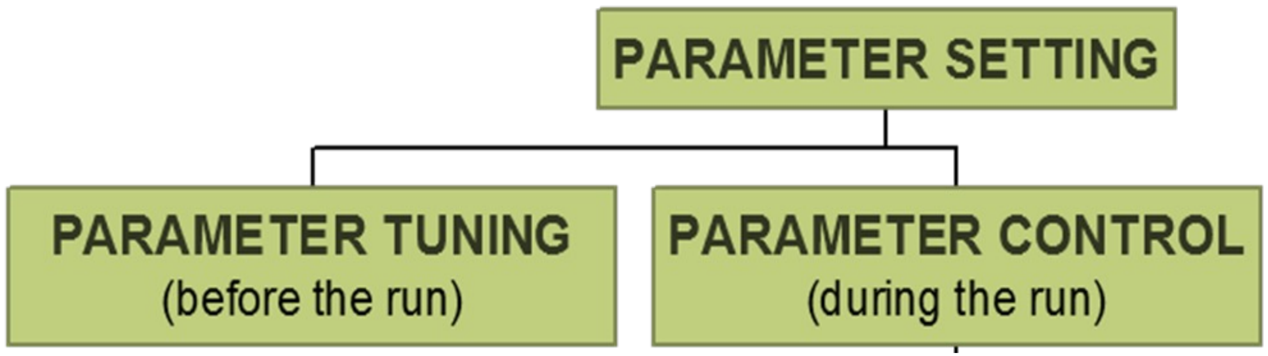
an EA is a dynamic, adaptive process

THUS

optimal parameter values may vary during a run

Q2: How to vary parameter values?

Parameter Setting



Varying mutation step size

Task to solve:

- min $f(x_1,\ldots,x_n)$
- L_i **<=** x_i **<=** U_i for $i = 1,\ldots,n$ bounds
- $g_i(x) \neq 0$ for $i = 1,\ldots,q$ inequality constraints
- $h_i(x) = 0$ for $i = q+1,\ldots,m$ equality constraints

Algorithm:

- EA with real-valued representation $(x_1,\ldots,x_n)$
- arithmetic averaging crossover
- Gaussian mutation: $x'_i = x_i + N(0, \boldsymbol{\sigma})$
- standard deviation $\boldsymbol{\sigma}$ is called mutation step size

Varying mutation step size, option 1

Replace the constant **σ** by a function **σ** (t)

$$\sigma(t) = 1 - 0.9 \times \frac{t}{T}$$

0 **<** *t* **<=** *T* is the current generation number

Features:

- changes in **σ** are independent from the search progress
- strong user control of **σ** by the above formula
- **σ** is fully predictable
- a given **σ** acts on all individuals of the population

Varying mutation step size, option 2

Replace the constant **σ** by a function **σ**(t) updated after every *n* steps by the 1/5 success rule, where p_s is the % of successful mutations:

$$\sigma(t) = \begin{cases} \sigma(t-n)/c & \text{if } p_s > 0.2 \\ \sigma(t-n)\cdot c & \text{if } p_s < 0.2 \\ \sigma(t-n) & \text{otherwise} \end{cases}$$

Features:

- changes in **σ** are based on feedback from the search progress
- some user control of **σ** by the above formula
- **σ** is not predictable
- a given **σ** acts on all individuals of the population

Varying mutation step size, option 3

- Assign a personal **σ** to each individual
- Incorporate this **σ** into the chromosome: (x_1, …, x_n, **σ**)
- Apply variation operators to x_i's and **σ**

$$\sigma' = \sigma \times e^{N(0,\sigma)}$$

$$x_i' = x_i + N(0,\sigma')$$

Features:

- changes in **σ** are results of natural selection
- (almost) no user control of **σ**
- **σ** is not predictable
- a given **σ** acts on one individual

Varying mutation step size, option 4

- Assign a personal **σ** to each variable in each individual
- Incorporate **σ**'s into the chromosomes: (x_1, …, x_n, $\boldsymbol{\sigma}_1$, …, $\boldsymbol{\sigma}_n$)
- Apply variation operators to x_i's and $\boldsymbol{\sigma}_i$'s

$$\sigma_i' = \sigma_i \times e^{N(0,\tau)}$$

$$x_i' = x_i + N(0,\sigma_i')$$

Features:

- changes in $\boldsymbol{\sigma}_i$ are results of natural selection
- (almost) no user control of $\boldsymbol{\sigma}_i$
- $\boldsymbol{\sigma}_i$ is not predictable
- a given $\boldsymbol{\sigma}_i$ acts on one gene of one individual

Varying penalties

Constraints

- $g_i(x) \neq 0$ for i = 1,…,q inequality constraints
- $h_i(x) = 0$ for i = q+1,…,m equality constraints

are handled by penalties:

eval(x) = f(x) + W × penalty(x)

where

$$penalty(x) = \sum_{j=1}^{m} \begin{cases} 1 & \textit{for violated constraint} \\ 0 & \textit{for satisfied constraint} \end{cases}$$

Varying penalties, option 1

Replace the constant W by a function W(t)

$$W(t) = (\mathrm{C} \times t)^{\alpha}$$

0 **<** t **<=** T is the current generation number

Features:

- changes in W independently from the search progress
- strong user control of W by the above formula
- W is fully predictable
- a given W acts on all individuals of the population

Varying penalties, option 2

Replace the constant W by W(t) updated in each generation

$$W(t+1) = \begin{cases} \beta \times W(t) & \text{if last k champions all feasible} \\ \gamma \times W(t) & \text{if last k champions all infeasible} \\ W(t) & \text{otherwise} \end{cases}$$

$\beta < 1$, $\gamma > 1$, $\beta \times \gamma \neq 1$, champion: best of its generation

Features:

- changes in W are based on feedback from the search progress
- some user control of W by the above formula
- W is not predictable
- a given W acts on all individuals of the population

Varying penalties, option 3

Assign a personal W to each individual

Incorporate this W into the chromosome: $(x_1, \ldots, x_n, W)$

Apply variation operators to x_i's and W

Alert:

$$eval((x, W)) = f(x) + W \times penalty(x)$$

while for mutation step sizes we had

$$eval((x, \boldsymbol{\sigma})) = f(x)$$

this option is thus sensitive "cheating" & makes no sense

Lessons learned (1/2)

Various forms of parameter control can be distinguished by:

- primary features:
  - what component of the EA is changed
  - how the change is made
- secondary features:
  - evidence/data backing up changes
  - level/scope of change

What component is controlled

Practically any EA component can be parameterized and thus controlled on-the-fly:

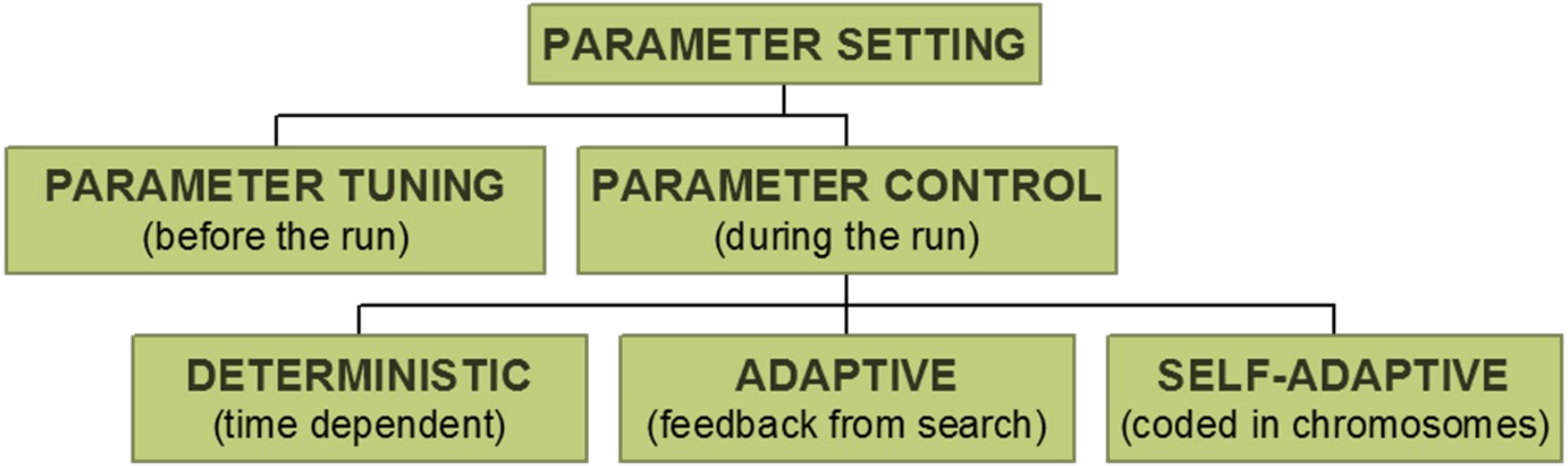
- representation
- evaluation function
- variation operators
- selection operator (parent or mating selection)
- replacement operator (survival or environmental selection)
- population (size, topology)

How are parameters controlled

Three major types of parameter control:

- deterministic: some rule modifies strategy parameter without feedback from the search (based on some counter)
- adaptive: feedback rule based on some measure monitoring search progress
- self-adaptative: parameter values evolve along with solutions; encoded onto chromosomes they undergo variation and selection

Global taxonomy – now well-founded ☺



Evidence: Informing the change (1/2)

The parameter changes may be based on:

- time or nr. of evaluations (deterministic control)
- population statistics (adaptive control)
  - progress made
  - population diversity
  - gene distribution, etc.
- relative fitness of individuals created with given values (adaptive or self-adaptive control)

Evidence: Informing the change (2/2)

- Absolute evidence: predefined event triggers change, e.g. increase p_m by 10% if population diversity falls under threshold x
- Direction and magnitude of change is fixed
- Relative evidence: compare values through solutions created with them, e.g. increase p_m by x% if top x% offspring came by high mutation rates, decrease otherwise
- Direction and magnitude of change is not fixed

Evidence: Refined taxonomy

- Combinations of types and evidences
  - Possible: +
  - Impossible: -

	Deterministic	Adaptive	Self-adaptive
Absolute	+	+	-
Relative	-	+	+

Scope/level

The parameter may take effect on different levels:

- environment (fitness function)
- population
- individual
- sub-individual

Note: given component (parameter) determines possibilities

Thus: scope/level is a derived or secondary feature in the classification scheme

Lessons learned (2/2)

Various forms of parameter control can be distinguished by:

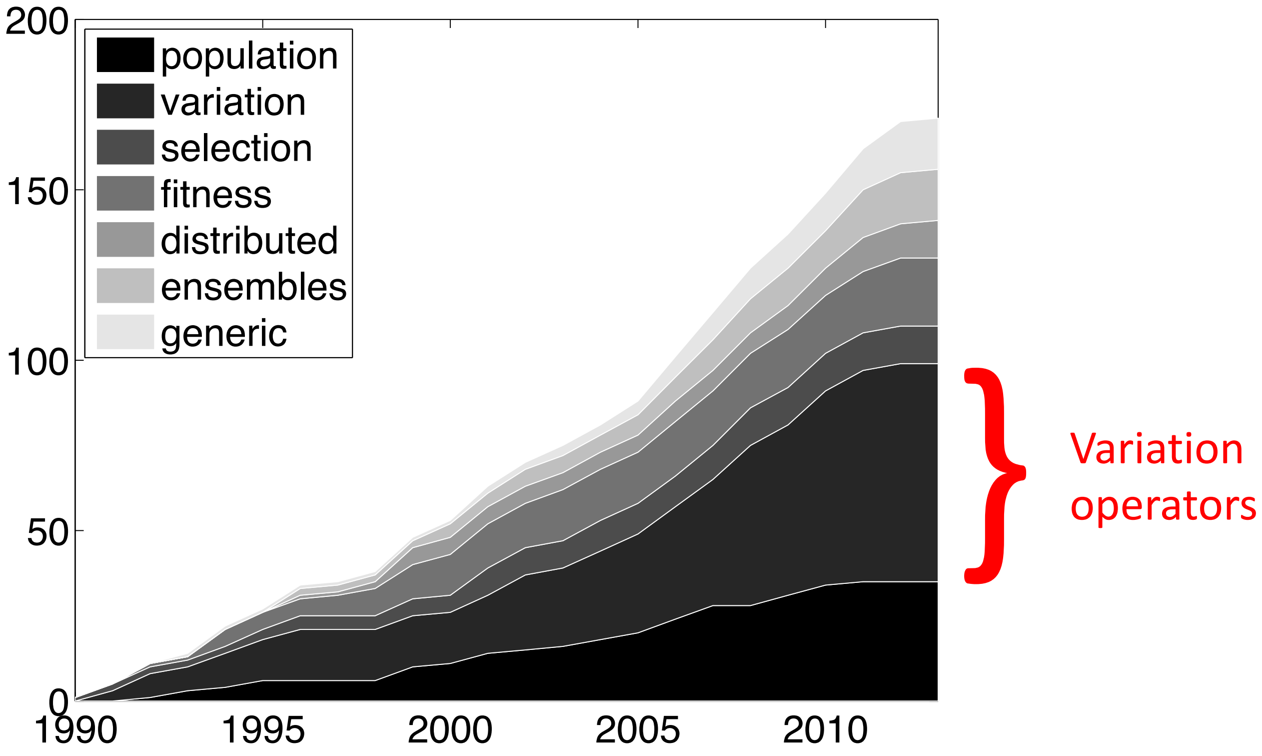
	$\sigma(t) = 1\text{-}0.9*t/T$	$\sigma' = \sigma/c$, if $r > 1/5$ ...	$(x_1, \ldots, x_n, \sigma)$	$(x_1, \ldots, x_n, \sigma_1, \ldots, \sigma_n)$	$W(t) = (C*t)^\alpha$	$W' = \beta * W$, if $b_i \in F$	$(x_1, \ldots, x_n, W)$
What	Step size	Step size	Step size	Step size	Penalty weight	Penalty weight	Penalty weight
How	Deterministic	Adaptive	Self-adaptive	Self-adaptive	Deterministic	Adaptive	Self-adaptive
Evidence	Time	Successful mutations rate	(Fitness)	(Fitness)	Time	Constraint satisfaction history	(Fitness)
Scope	Population	Population	Individual	Gene	Population	Population	Individual

Evaluation/Summary

- Parameter control offers the possibility to use appropriate values in various stages of the search

- Adaptive and self-adaptive parameter control
  - offer users “liberation” from parameter tuning
  - delegate parameter setting task to the evolutionary process
  - the latter implies a double task for an EA: problem solving + self-calibrating (overhead)

Publications per category overview



G. Karafotias, M. Hoogendoorn, and A.E. Eiben, [Parameter Control in Evolutionary Algorithms: Trends and Challenges](), *IEEE Transactions on Evolutionary Computation*, 19(2):167-187, 2015