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INF3490 – Evolvable Hardware
Cartesian Genetic Programming

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Overview


- Introduction to Evolvable Hardware (EHW)
- Cartesian Genetic Programming
- Applications of EHW

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Evolvable Hardware (EHW)

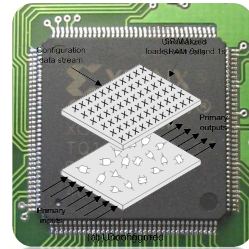
- Hardware systems designed/ modified automatically by EAs
- A string of symbols/bits is evolved by an EA and translated into a HW system
- Offline EHW
 - Solutions are simulated in a PC
- Online EHW
 - Solutions are tested on target HW



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EHW

- FPGA
 - Reconfigurable hardware chip
 - Useful for online EHW
- On-chip evolution
 - EA running on the target chip, together with solutions
- Run-time adaptable EHW
 - Evolution can modify the system during operation




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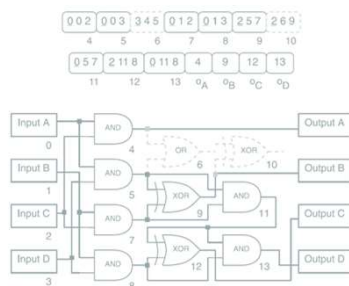
Applications of EHW

- Pattern recognition / classification circuits
- Digital image filters
- Evolution of analog circuits
- Cache mapping functions
- On-the-fly compression for printers
- Spacecraft antenna



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CARTESIAN GENETIC PROGRAMMING

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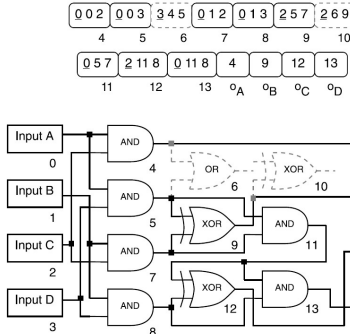
Cartesian Genetic Programming (CGP)

- A type of Genetic Programming
- Allows restrictions compared to general GP:
 - Integer genome
 - Tree nodes are mapped to a grid
 - Connectivity can be restricted
- Popular in Evolvable Hardware applications
 - But can be used for many other things as well

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Example structure: Digital circuit



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CGP genome

- Internal node genes:
 - Node type: index to lookup table of functions
 - Inputs: index of other nodes
 - Optional: additional parameters
- Output node gene:
 - Internal node index

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CGP parameters

- Columns: n_c
- Rows: n_r
- Levels-back: l
 - How many of the previous columns a node can connect to
- Columns x rows defines the maximum number of nodes in the graph

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General structure

Genome: $F_0 C_{0,a} \dots C_{0,a} F_1 C_{1,0} \dots C_{1,a} \dots F_{(c+1)} C_{(c+1),0} \dots C_{(c+1),a} O_0 O_1 \dots O_m$

node function gene connection gene outputs

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Advantages of CGP

- Easy implementation
 - Fixed genome size and simple representation
 - Simple mutation and crossover
- Bloat is restricted
 - The number of nodes is restricted
- Regular structure suitable for e.g. hardware implementation
 - A grid structure with limited connectivity ideal for HW routing

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Other features of CGP

- Reuse of parts of the tree is possible
- Allows multiple outputs
- Parts of the genome may be non-coding
 - This has an analogy in biology, where only a fraction of the DNA is composed of *exons* ("coding" genes).
 - The other part is called *introns* (non-coding genes, sometimes called "junk" DNA). It is however believed that these are useful for something.
 - Likewise, the genetic redundancy (neutrality) in CGP is thought to be positive for the evolutionary search.

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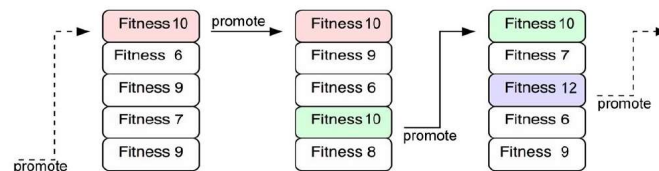
Genetic operations in CGP

- Mutation
 - Select randomly a number of genes to mutate
 - Change to new (valid) random values
- Crossover
 - One-point crossover or other variants directly on the genome
- Usually only mutations are used
 - Many applications find crossover to have a destructive effect - it disrupts the tree structure too much

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Evolution in CGP

- The most popular is a variant of ES called (1+4) ES
- Choose children which have \geq fitness than parent



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CGP can code:

- Circuits
- Mathematical functions / equations
- Neural networks
- Programs
- Machine learning structures
- ...

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Example: Art



- Inputs: image pixel position x, y
- Outputs: r,g,b intensities per pixel
 - Or single monochrome intensity

$$r = f1(x, y)$$

$$g = f2(x, y)$$

$$b = f3(x, y)$$

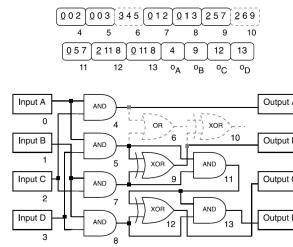
Function gene	Function definition
0	x
1	y
2	$\sqrt{x+y}$
3	$\sqrt{ x-y }$
4	$255(\sin(\frac{\pi}{256}x) + \cos(\frac{\pi}{256}y))/2$
5	$255(\cos(\frac{\pi}{256}x) + \sin(\frac{\pi}{256}y))/2$
6	$255(\cos(\frac{\pi}{256}x) + \sin(\frac{\pi}{256}y))/2$
7	$\exp(x+y) \pmod{256}$
8	$ \sinh(x+y) \pmod{256}$

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Example: Evolvable Hardware 1

- Evolution of combinational circuit, e.g. multiplier
- 2-bit multiplier:
 - 2x2=4 inputs
 - 4 outputs
- Fitness:
 - # correct output combinations (of 16)

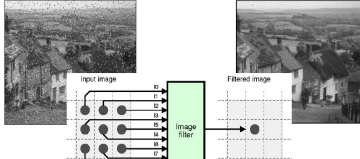


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Example: Evolvable Hardware 2

- Evolution of digital image filters
- Input: distorted image
- Output: filtered image
- Fitness: distance between filtered and original image

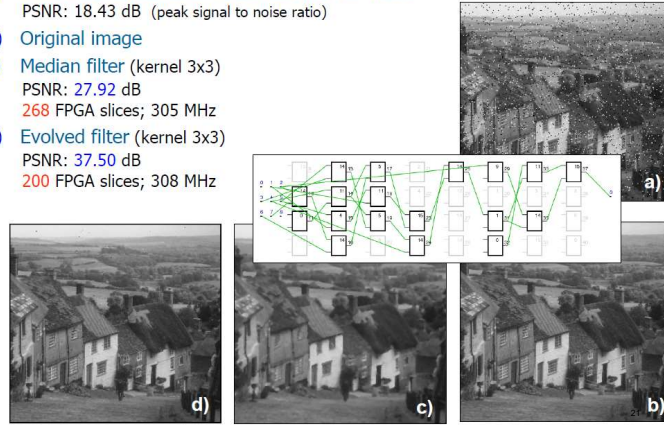


Number	Function	Description
0	$x \vee y$	binary or
1	$x \wedge y$	binary and
2	$x \oplus y$	binary xor
3	$x + y$	addition
4	$x + y^2$	addition with saturation
5	$(x + y) >> 1$	average
6	$Max(x, y)$	maximum
7	$Min(x, y)$	minimum

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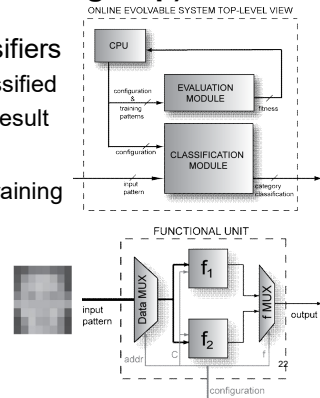
Example result (Slide from Sekanina)

- a) Image corrupted by 5% salt-and-pepper noise
PSNR: 18.43 dB (peak signal to noise ratio)
- b) Original image
- c) Median filter (kernel 3x3)
PSNR: 27.92 dB
268 FPGA slices; 305 MHz
- d) Evolved filter (kernel 3x3)
PSNR: 37.50 dB
200 FPGA slices; 308 MHz



Example: EHW 3 (ROBIN group)

- Evolution of HW classifiers
 - Input: signal to be classified
 - Output: classification result
- Fitness:
 - # correctly classified training samples
- Ensemble model
- On-chip system

**Challenges of EHW**

- Scalability – It's hard to evolve large systems!
 - General challenge in EC
 - Evolution of larger combinational circuits is difficult
 - Large *and* difficult search space
 - Time-consuming fitness function
 - 4x4 multiplier is hard
- On-chip evolution
 - Less flexibility offered by HW
 - Reconfiguration can be challenging



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INF3490 – Swarm Intelligence
Particle Swarm Optimization



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Overview

- Introduction to swarm intelligence principles
- Particle Swarm Optimization (in depth)
- Stigmergy, pheromones, and ACO (briefly)
- Swarm robotics (briefly)

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Swarms in nature

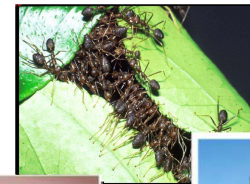


<http://youtu.be/kdECYXdW9Tc>

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Fish, birds, ants, termites, ...

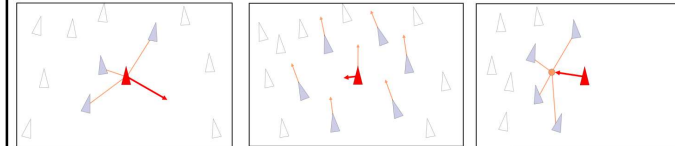


Key features

- Simple local rules
- Local interaction
- Decentralized control
- Complex global behavior
 - Difficult to predict from observing the local rules
 - *Emergent* behavior

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Flocking model – “boids”



Separation – avoid crowding

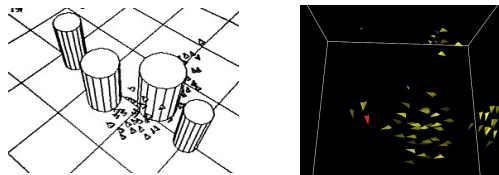
Alignment – steer towards average heading

Cohesion – steer towards average position

Only considering the boid's neighborhood

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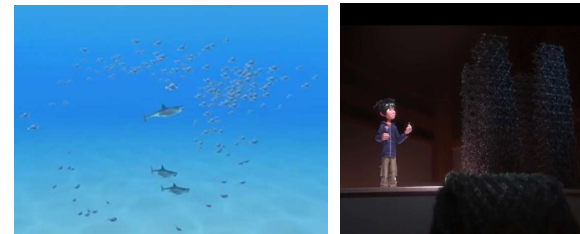
Result - boids

Original: <http://youtu.be/86iQiV3-3IA>

Netlogo: “Flocking 3D Alternate” model

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Application: Computer graphics

https://youtu.be/UM8SzF6_0sM<https://youtu.be/ttxXH4WkrJM?t=1m46s>

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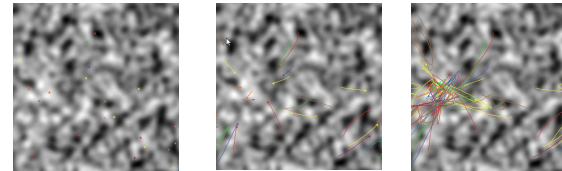
Applications in bio-inspired computing

- **Particle swarm optimization**
 - Parameter optimization
- **Ant colony optimization**
 - Graph-based optimization problems (e.g. TSP)
- **Artificial immune systems**
 - Classification, anomaly detection
- **Swarm robotics**
 - Achieve complex behavior in robotic swarms through simple local rules

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Particle Swarm Optimization (PSO)

- Optimizes a population of solutions
 - A *swarm of particles*



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Principle

- Evaluate your present position
- Compare it to your previous best and neighborhood best
- Imitate self and others

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Simplified PSO algorithm

- For each particle i in the swarm
 - Calculate fitness
 - Update local best
 - Find neighborhood best
 - Update velocity
 - Update position

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PSO update formulas

For each dimension d in particle i :

1. Velocity update

$$v_{id}^{(t+1)} \leftarrow \underbrace{\alpha v_{id}^{(t)}}_{\text{inertia}} + \underbrace{U(0, \beta)}_{\text{random}} \underbrace{(p_{id} - x_{id}^{(t)})}_{\text{direction personal best}} + \underbrace{U(0, \beta)}_{\text{random}} \underbrace{(p_{gd} - x_{id}^{(t)})}_{\text{direction neighborhood best}}$$

2. Position update

$$x_{id}^{(t+1)} \leftarrow x_{id}^{(t)} + v_{id}^{(t+1)}$$

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What happens?

- A particle circles around in a region centered between the bests of itself and its neighbors
- The bests are updated and the particles cluster around better regions in the search space
- The way good solutions are propagated depends on how we define the neighborhood

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Neighborhood topologies

- *gbest*: all particles are connected
 - Every particle gets information about the global best value
 - Can converge (too) fast
- *lbest*: connected to K nearest neighbors in a wrapped population array
 - Slower convergence, depending on K
 - More areas are searched in parallel
- Several other topologies exist

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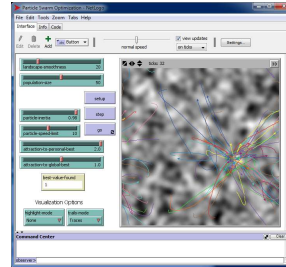
PSO parameters

- Particle:
 - Usually a D-dimensional vector of real values
 - Binary variant exists
- Swarm size: usually $10 < N < 100$
- Recommended $\alpha = 0.7298$
- Recommended $\beta = 1.4961$

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Parameter experimentation

- NetLogo
 - Particle Swarm Optimization model
- Model uses *gbest* neighborhood
- Download and try



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Advantages of PSO

- Few parameters
- Gradient free
- Decentralized control (depends on variant.)
- Simple to understand basic principle
- Simple to implement

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PSO vs. Evolutionary Algorithms

- Both are population based
- PSO: No selection – all particles survive
- Information exchange between solutions:
 - PSO: neighborhood best
 - GA: crossover (and selection)

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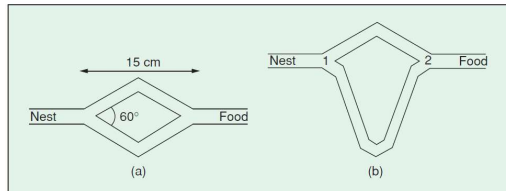
PSO applications

- Similar application areas as EAs
 - Most optimization problems
- Image and video analysis
- Electricity network optimization
- Neural networks
- ...

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Stigmergy

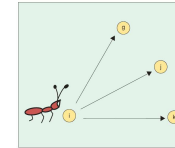
- Ants deposit a substance called *pheromone* when walking to and from food sources
 - Other ants can sense this and follow the same path
- This kind of communication through the environment is called *stigmergy*



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Ant Colony Optimisation (ACO)

- Inspired by ants' use of pheromones
- Ants construct solutions in a graph
 - Probability of choosing a new edge is proportional with its pheromone level
- Pheromone update on edges
 - (Good) solutions deposit pheromones
 - Old pheromones evaporate



ACO applications

- Telecommunication networks
- Scheduling problems
- Vehicle routing (truck fleet)
- ...
- Further reading:
M. Dorigo et al, *Ant Colony Optimization – Artificial Ants as a Computational Intelligence Technique*,
IEEE Computational Intelligence Magazine, Nov. 2006

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Swarm robotics

- Inspired by nature's swarms
 - Simple rules
 - Local interaction
 - Decentralized control
 - Complex global behavior (soon?)
- Advantages
 - Cheap components
 - No single point of failure
 - Many configurations possible
- Possible applications
 - Search and rescue
 - Remote area exploration
 - Construction



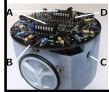
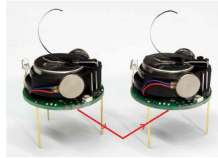
<https://youtu.be/NDITqQ7xbWQ>



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Swarm robotics examples

- **Swarmbot** <http://youtu.be/h-2D-zlU-DQ>
 - Collaborating robots
- **TERMES** <http://youtu.be/tCJMG0Jnode>
 - Termite-inspired algorithmic self-assembly
- **Kilobot** <https://youtu.be/xK54Bu9HFRw?list=PLC7119C2D50BEA077>
 - Large scale swarm, very simple control and communication
- **Nano Quadrotors** <https://youtu.be/YQIMGV5vtd4>
 - Flocking-like rules for formation flying



CHIRP (NTNU)

