A Synthetic review of Evolutionary algorithms and their applications in image analysis

Workshop on Machine-Learning-Assisted Image Formation
nice,

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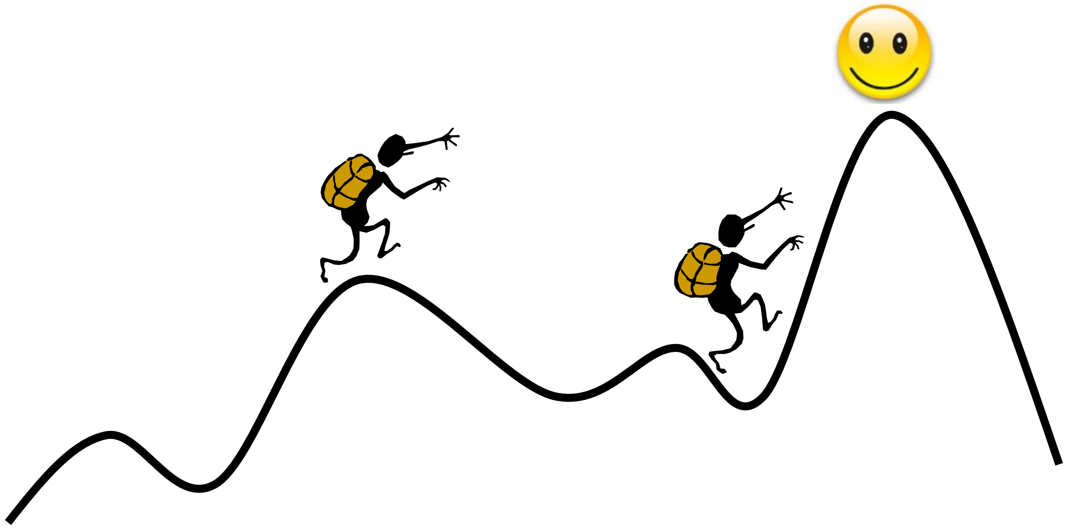
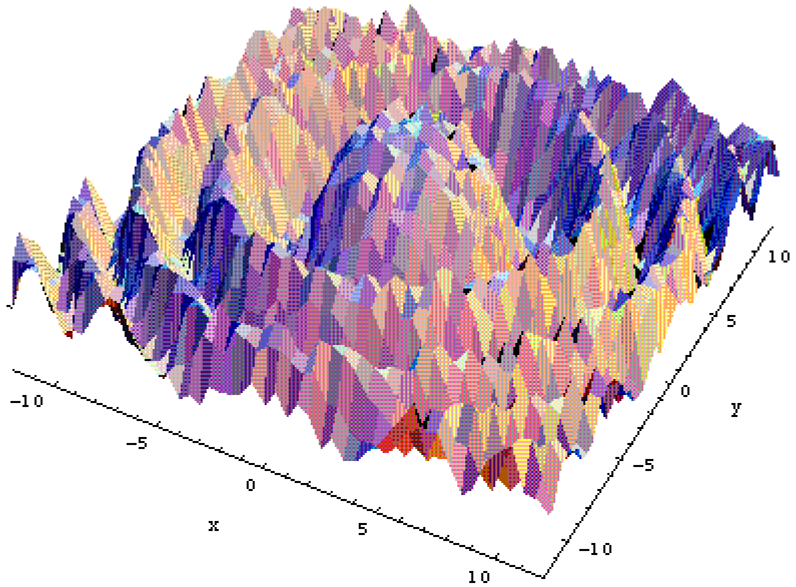
Agenda

- Evolutionary algorithms: general introduction
- Genetic algorithms: principle and basic algorithm
- Particle swarm optimization: principle and basic algorithm
- Multi objective Algorithms: few words
- Applications in image: several cases
- Conclusion

The problem

- Many interesting optimization problems are not trivial.
  - The optimal solution cannot always be found in polynomial time.





-Multimodal
-The size of the search space grows exponentially!

The Optimization Problem

- **Exact algorithms: brute force, branch and bound…optimal solutions if no limit on time and memory**
- **Deterministic Methods** can fail because they could converge to local optimum
- **Heuristic algorithms: ant colony, genetic algorithms… do not guarantee but they can give good answers relatively quickly**
- **Evolutionary Algorithms** can however fail because they could converge to a sub-optimal solution
- Analogy: read a book in 1 month or 5 days

Solution: Parallel search concept

- Conduct searching in different areas simultaneously.
  - Population Based
  - Avoid unfortunate starting positions.
- Employ heuristic methods to effectively explore the space.
  - Focus on promising areas.
  - Also keep an eye on other regions.
- This is where EAs come into play!

Eas are Interesting for optimization and classification

- Can be used to solve many problems, and many kinds of problems, with minimal adjustments, without knowing optimum
- Are fast and easy to implement

“Dialects” Developing in Artificial Intelligence

- Fogel Owens (USA, 1965) **Evolutionary Programming** (fixed structure)
- Holland Genetic Algorithms (USA, 1973) **Genetic Algorithm**
- Rechenberg Schwefel (Germany, 1973) **Evolution Strategies**
- **90s Evolutionary Algorithms (EA)**
- **EA Family: GA** (genetic algorithms), PSO (particle swarm optimization), ACO (ant colony), BCO (bee colony), (GWO) grey wolf (2014), CSO (cuckoo search) (2009) , GSA (gravitational search algorithm) (2009) …
- DE: Differential Evolution (new candidates: by combining existing ones)
- EDA: Estimation of Distribution Algorithm (heuristics, GA, sampling)
- Memetic algorithms (hybrid)

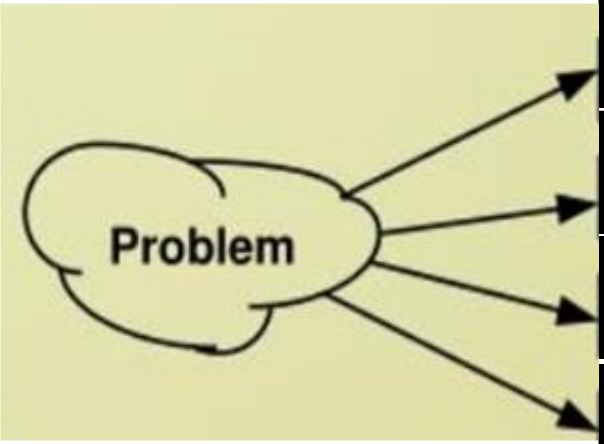
Some assertions

- **Culture and Cognition Summary**
  - Individuals searching for solutions learn from the experiences of others (individuals learn from their neighbors)
  - An observer of the population perceives phenomena of which the individuals are the parts (individuals that interact frequently become similar)
  - Culture affects the performance of individuals that comprise it (individuals gain benefit by imitating their neighbors)

- **So, what about intelligence?**
  - Social behavior increases the ability of an individual to adapt
  - There is a relationship between adaptability and intelligence
  - Intelligence arises from interactions among individuals

Framework

- Search is directed toward regions that are *likely* to have higher fitness values, through metaheuristics

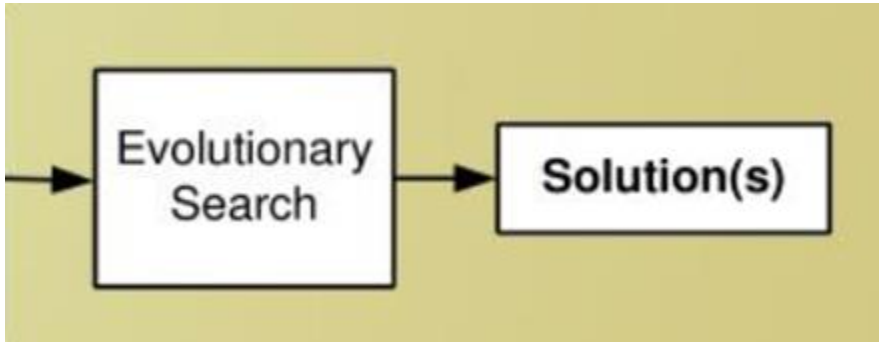


Coding of solution

Objective function

Operators

Knowledge

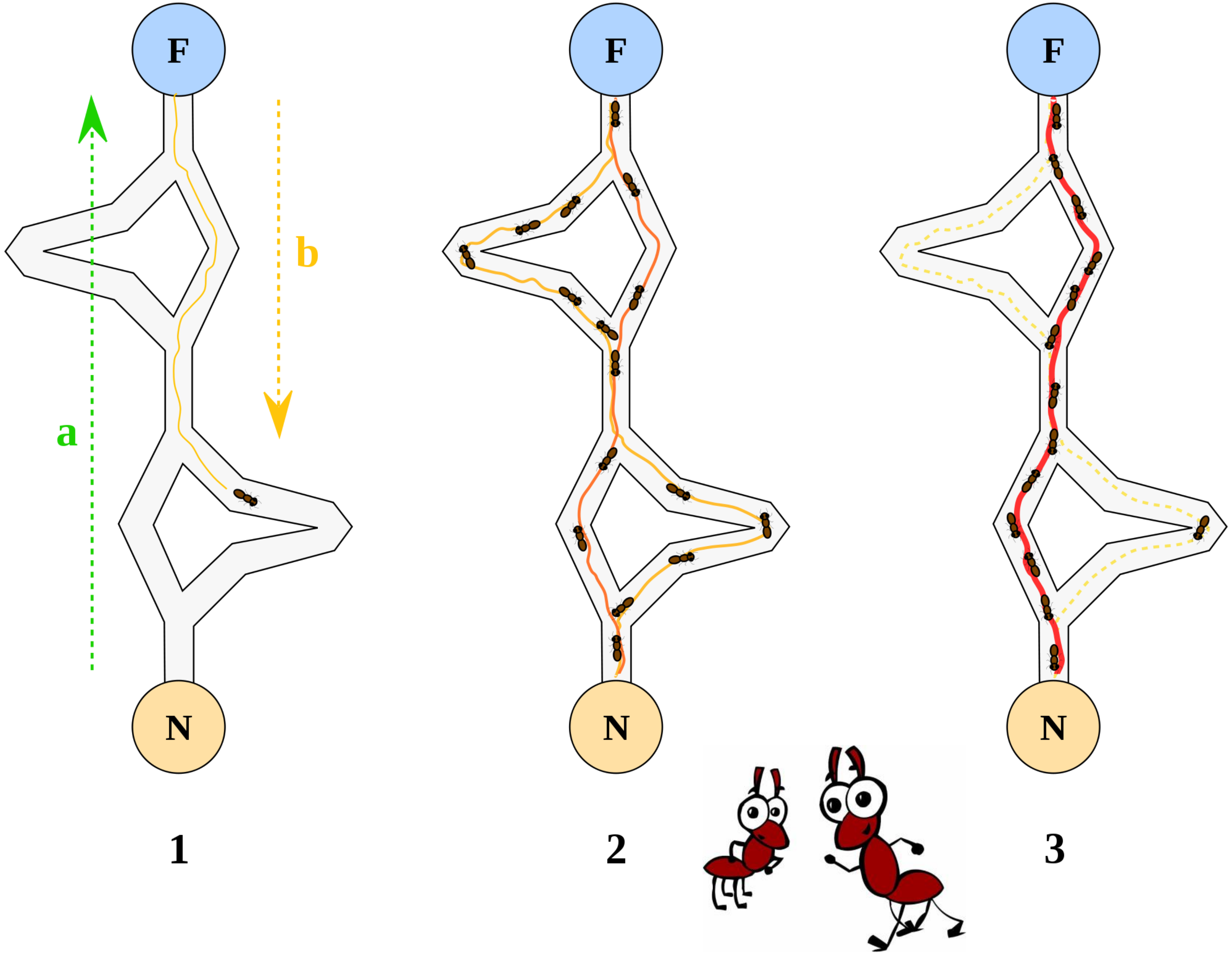


Problem Encoding

Implementation

Differences to classical algorithms: parallel search, straightforward to apply (direct fitness), able to apply self adaptation, use probabilistic rather than deterministic transition rules, several solutions can be provided.

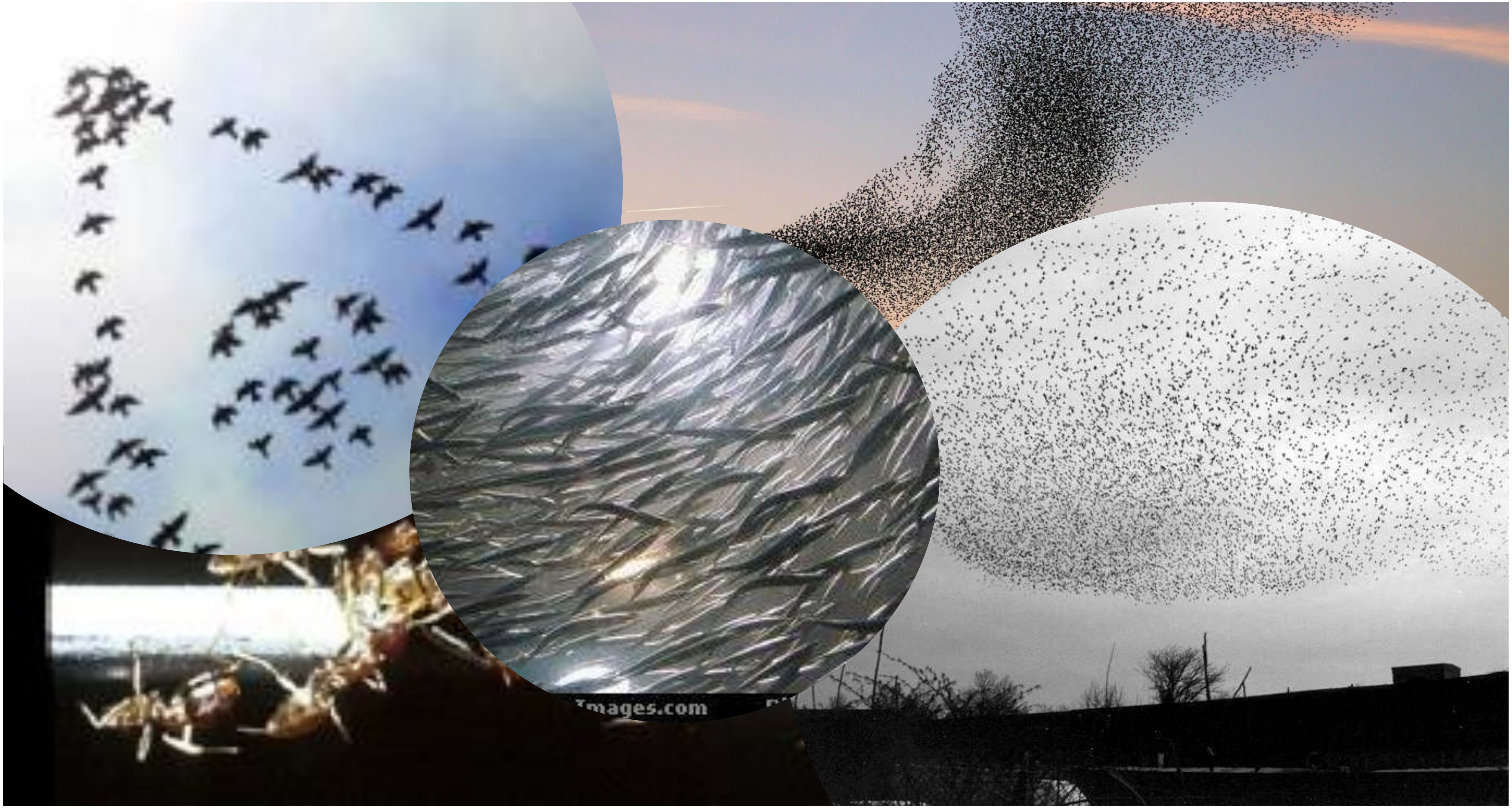
Ant Colony Optimization (concept)



The main inspiration of the ACO algorithm comes from stigmergy.

Stigmergy refers to the interaction and coordination of organisms in nature by modifying the environment.

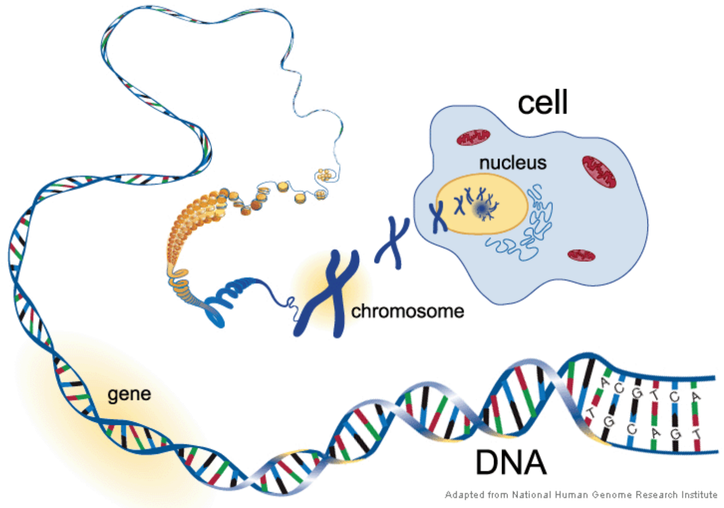
The key points: no centralized control, probabilistic approach



Genetic algorithms

Genetic algorithms

It is one of several evolutionary algorithms incorporating the idea of sexual reproduction, or « genetic recombination »



Background

Charles Darwin1859: Writes Origin of Species and rocks the worlds of science and philosophy

Nils Aall Barricellu 1954: First emulates evolution on a computer

Ingo Rechenberg 1960s: Popularizes genetic algorithms as a tool for optimization

Holland 1975s: artificial systems

Genetic algorithms

It is inspired by the natural selection and mimics the biological evolution

We start from a group of solutions (initial population). Those solutions are then combined to produce the offsprings- the next generation of (probably) better solutions.

New solutions are made from old ones using
Crossover,
Mutation and Selection
just like Nature does.

Genetic algorithms

Biggest advantage: You do not need to know how to solve the problem.
You just have to be able to evaluate the quality of the generated solution coming and through iteration you get good solution.

Evolution and selection process: Almost same for all kind of problem

Fitness function and chromosome design: problem specific

Basic components of genetic algorithms

- **Representation**
  - How to encode the parameters of the problem?
  - Binary Problems
    - 10001 00111 11001 …..
  - Continuous Problems (vector, matrix…)
    - 0.8 1.2 -0.3 2.1 …..
  - Hybrid: 001100 0.8 1.2 -0.3 2.1 …..
  - Matrices, graphs…

- **Population**
  - A set of individuals
  - GAs maintain and evolve a population of individuals.
  - Parallel Search → Global Optimization

- **Fitness function**

- Gives a score to each state

Selection Strategy

Which chromosomes should be involved in reproduction?

Which offspring should be able to survive?

Several approaches: roulette, tournament, generation gap approach, elitist…

Genetic Operators

Crossover:

Exchange genetic materials between two chromosomes.

Mutation:

Randomly modify gene values at selected locations.

Fitness function

Solution representation

- The fitness function produces the next generation of stages
- The fitness function gives a score to each state
- The probability of being chosen for reproduction is based on the fitness score.

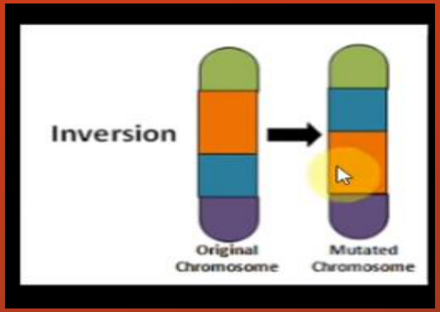
$f(x,y) = x^2y + 5xy - 3xy^2$

for what integer values of *x* and *y* is *f(x,y)* minimal? Direct

Feature selection for classification Direct (based on classifier) Direct

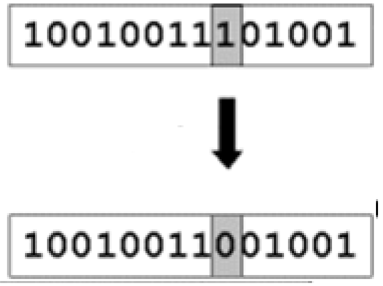
Clustering: hybrid chromosome and cost function Direct

TPS problem: indirect



Mutation

- The chromosome is subjected to a random small modification without interaction with the others

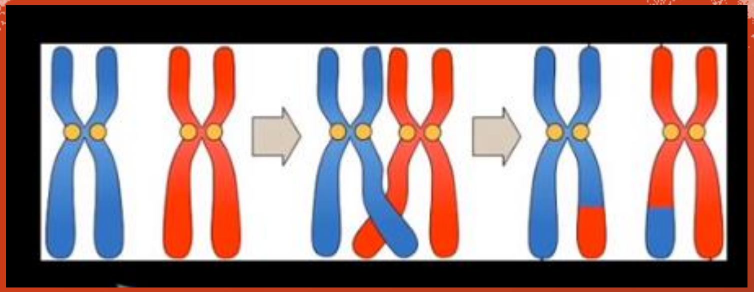


For binary representation

$y' = y\,(1 +/- N(0,\sigma))$

Non binary representation

- For other representations (matrix, graphs..), the operator depends on domain knowledge.



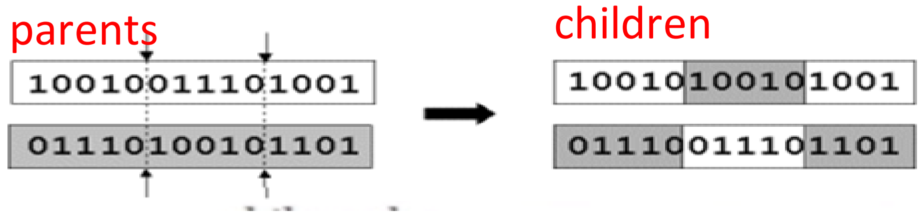
Crossover

ch'1 = a*ch1 + b*ch2
ch'2 = b*ch1 + a*ch2

Example for non binary representation

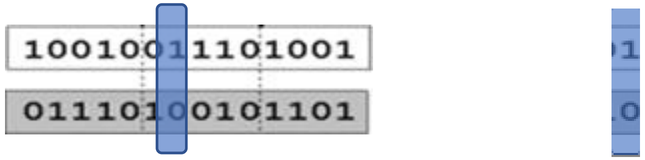
Binary representation (classic)

- For each pair to be mated, a crossover point (or more) is chosen at random from within the chromosome (binary).
- Offspring are created by exchanges between the parents at the crossover point.



Uniform crossover (ith allele)

ch' 1(i)=ch1(i) and ch'2(i)=ch2(i) if $p_i>0.5$
ch'1(i)=ch2(i) and ch'2(i)=ch1(i) if $p_i<0.5$



$p_7>0.8$

Reproduction

Roulette
Tournament
Gap approach
Elitist approach

"Only the strongest survive"
"Some weak solutions survive"

Popular approaches:

Baker's method: Use roulette wheel with *n* pointers spaced 1/*n* apart; use normalized fitness; spin wheel *once*.

Tournament selection - Select two individuals at random; the individual with the higher fitness is selected for the next population

Generation gap approach: Replace *x* percent that have worst fitness values (*x* is defined as the generation gap)

Elitist strategy: ensures that individual with highest fitness is copied into next generation (most GAs use this)

Genetic algorithms: parameters

The crossover rate

- The crossover operator is applied with a probability P_c.
- The higher is the rate the more novel chromosomes are introduced

The mutation rate

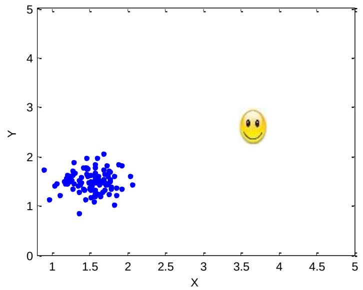
- The mutation operator is applied with a probability P_m.
- If too big, the search is random, the evolution process is disrupted.
- If too small less diversification and then stagnation risk.

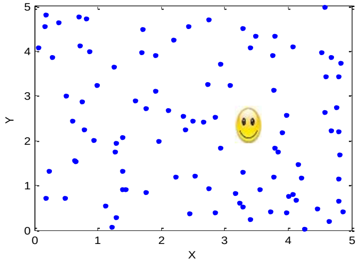
The population size

- **If too high**
  Diversity grows but slow convergence rate, Convergence toward a local optimum diminishes
- **If too small**
  Risk of premature convergence (local minimum)

Stopping criterion

A minimum score, number of generations, time…





Exploration versus exploitation

A few more words

- **No so easy!**
  - So called “optimal” parameter values do not exist!
  - Vary from problems to problems.
  - Need some trials to find suitable parameter values.
- **Randomness**
  - Inherently stochastic algorithms
  - Independent trials are needed for performance evaluation.
- **Why does it work?**
  - Easy to understand & implement (No maths required!)
  - Very difficult to analyse mathematically.
  - Converge to global optimum with probability 1 (infinite population).

- **The addons!**
- Multi – chromosomes: difficulty to « code » the problem
- Niching / Sharing: facilitate the maintain of the diversity
- Auto-adaptatif (Pmut, Pcross, population, chromosome, ...)
- Hybridation: a local algorithm is used to promote a subset of candidate.

Basic Framework

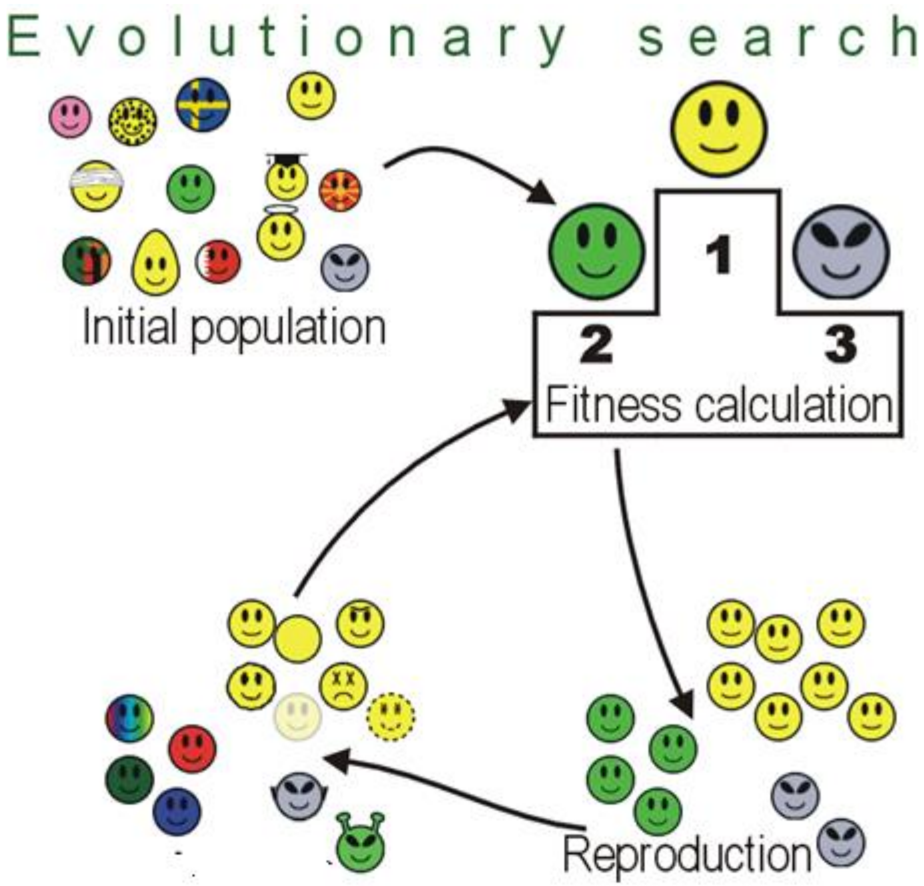
Initialization: Generate a random population P of n chromosomes

Evaluation: Evaluate the fitness $f(x)$ of each chromosome

Repeat until the stopping criteria are met:

- **Reproduction:** Repeat the following steps until all offspring are generated
  - **Parent Selection:** Select parents from P
  - **Crossover:** Apply crossover on the parents with probability P_c
  - **Mutation:** Apply mutation on offspring with probability P_m
  - **Evaluation:** Evaluate the newly generated offspring
- **Offspring Selection:** Create a new population from **offspring** and **P**

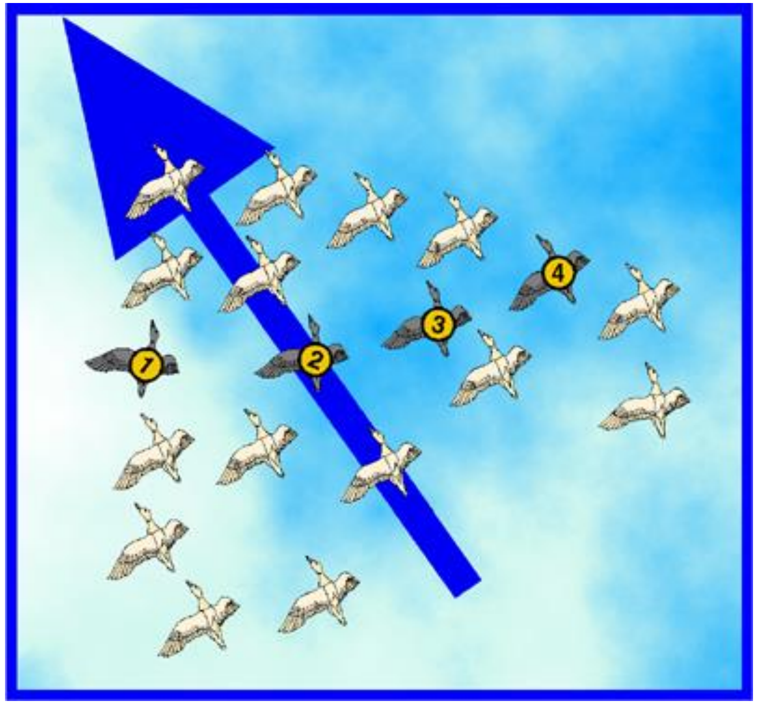
Output: Return the best individual found

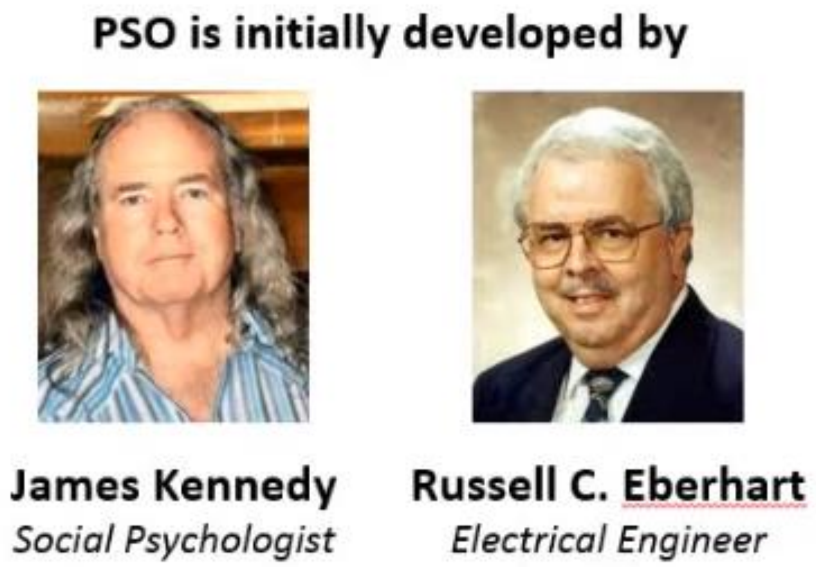


Picture inspired from Dr. Bo Yuan

Partical Swarm Optimization

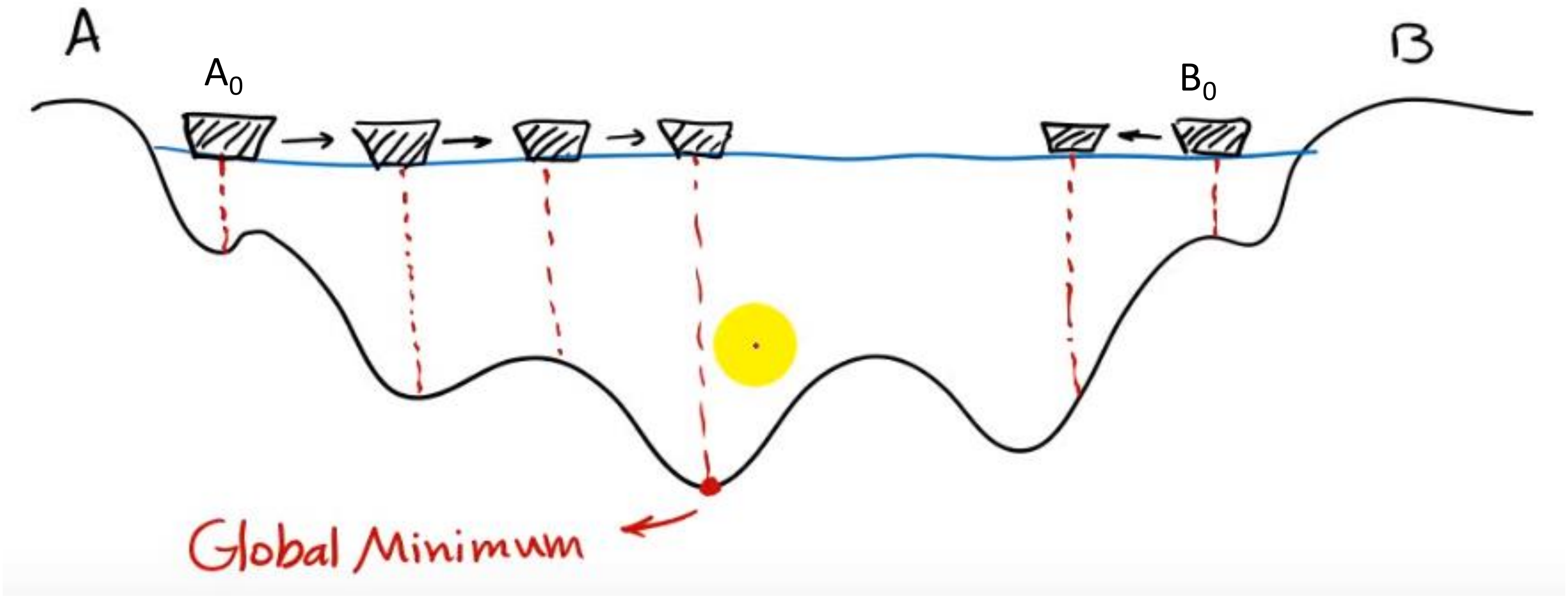
The Particle Swarm Optimization Algorithm





The DNA: combines <u>self-experiences</u> with <u>social experiences</u>

Intuition of PSO



Inspired from particle Swarm Optimization in MATLAB - Yarpiz Video

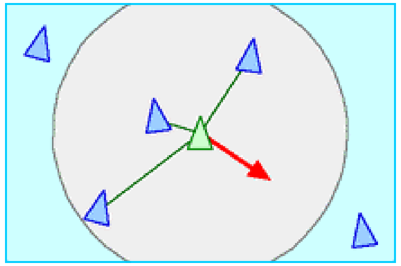
PSO Origin & Concept

In 1986, Craig Reynolds described this process in 3 simple behaviors of bird, fish..

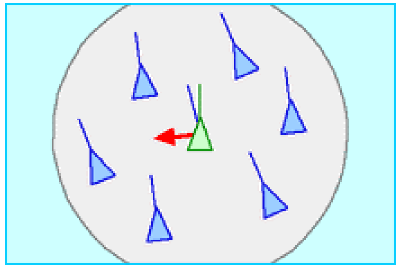
Uses a number of **agents** (**particles**) that constitute a swarm moving around in the search space looking for the best solution

Each particle in search space adjusts its "flying" according to its own **flying experience** as well as the flying experience of **other particles**

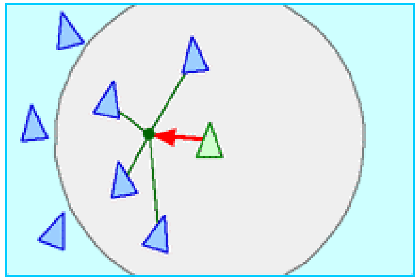
Each particle modifies its position according to: its current position, current velocity, the distance between its current position, its best position ***pbest***, the distance between its current position and the best position ***gbest***



1. Separation



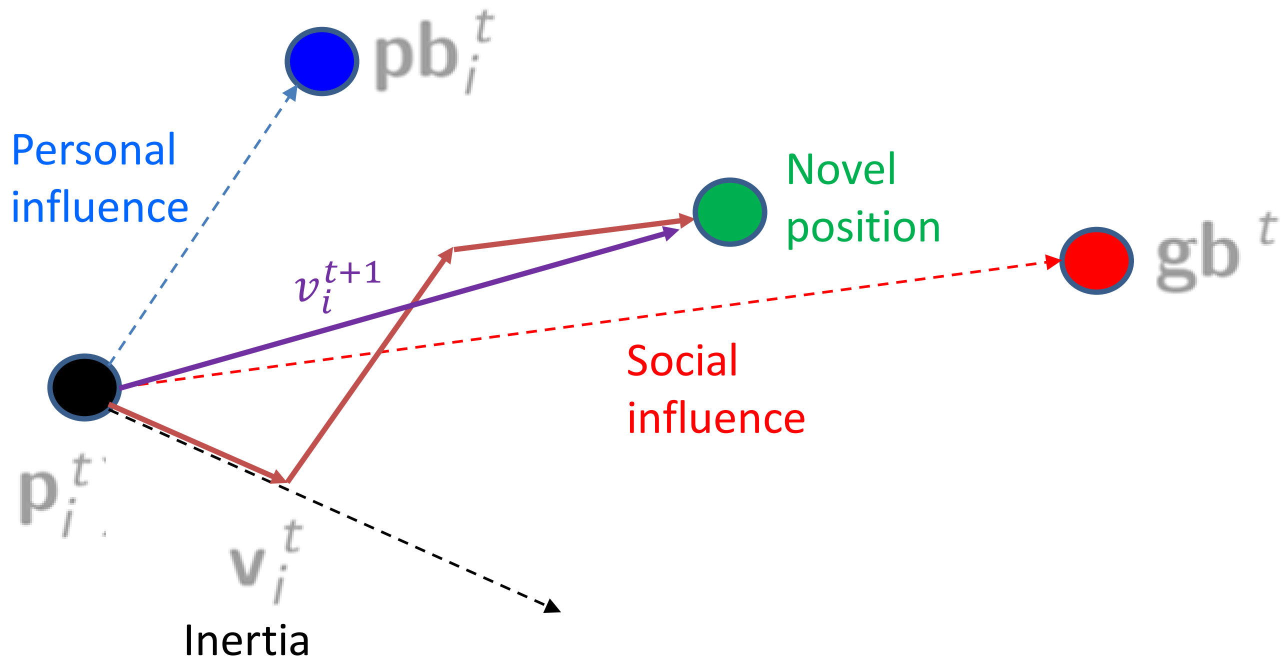
2. Alignment



3. Cohesion

PSO: concept and framework

Initialize the controlling parameters α, β, γ
Initialize the population
do
    for each particle
        Calculate the fitness of the particle
        Update pbest *if required*
        Update gbest *if required*
    end for
    Update the inertia weight (option)
    for each particle
        Update the velocity (v)
        Update the position (p)
    end for
while the end condition is not satisfied



$$v_i^{t+1} = \alpha v_i^t + \beta(pb_i^t - p_i^t) + \gamma(gb^t - p_i^t)$$

$$p_i^{t+1} = p_i^t + v_i^{t+1}$$

Inertia: Makes the particle move in the same direction and with the same velocity

Personal influence: Makes the particle return to a previous position, better than the current conservative

Social influence: Makes the particle follow the best neighbors' direction

Algorithm Characteristics

- **Advantages**
  - Insensitive to scaling of design variables
  - Simple implementation
  - Easily parallelized for concurrent processing
  - Derivative free
  - Very few algorithm parameters
  - Very efficient global search algorithm

- **Disadvantages**
  - Tendency to a fast and premature convergence in mid optimum points
  - Slow convergence in refined search stage

Adons

Adaptive PSO, Adaptive Mutation PSO

Adaptive PSO Guided by Acceleration Information

Attractive Repulsive Particle Swarm Optimization

Chaotic PSO, fuzzy PSO…

Cooperative Multiple PSO

Dynamic and Adjustable PSO

Extended Particle Swarms, hybrid

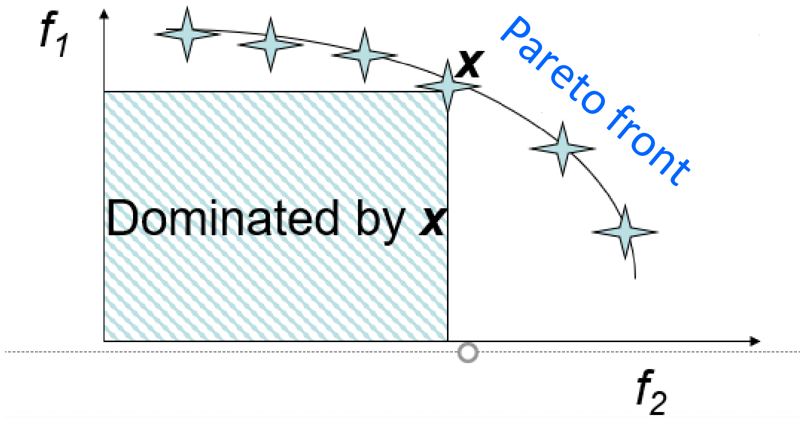
Few words about multi objective

Multi objectives: few words

- Extension of regular EA which maps multiple objective values to single fitness value
- Objectives typically conflict
- In a standard EA, an individual **A** is said to be better than an individual **B** if **A** has a higher fitness value than **B**
- In a MOEA, an individual **A** is said to be better than an individual **B** if **A** ***dominates*** **B**

An individual **A** is said to dominate individual **B** iff:

- **A** is no worse than **B** in all objectives
- **A** is strictly better than **B** in at least one objective

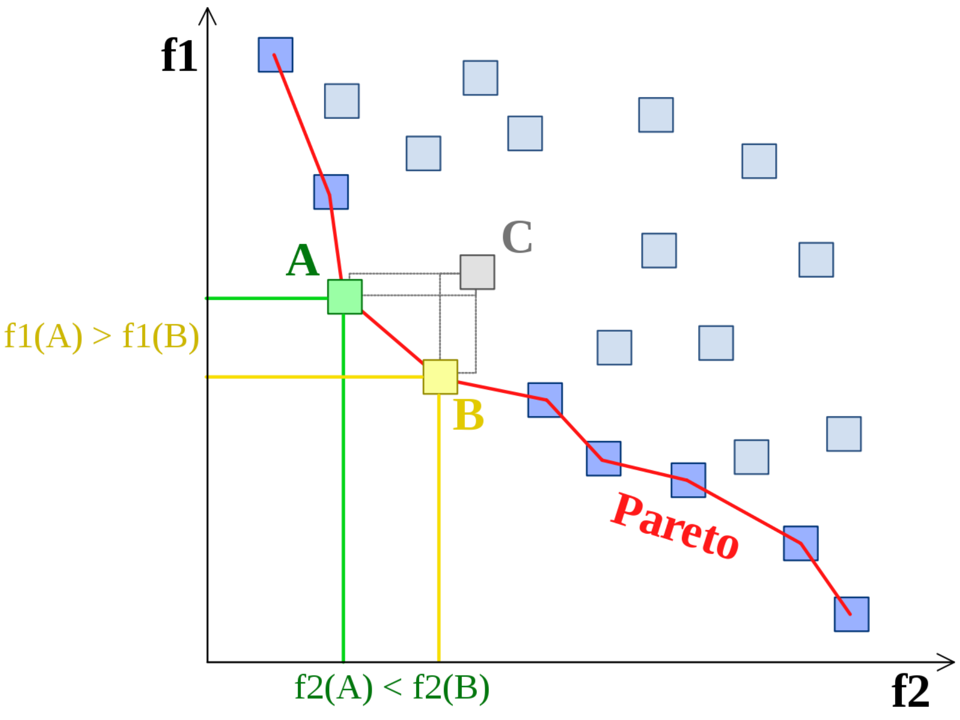


Multi objectives

- **The process:** update the individuals for Pareto Improvement.

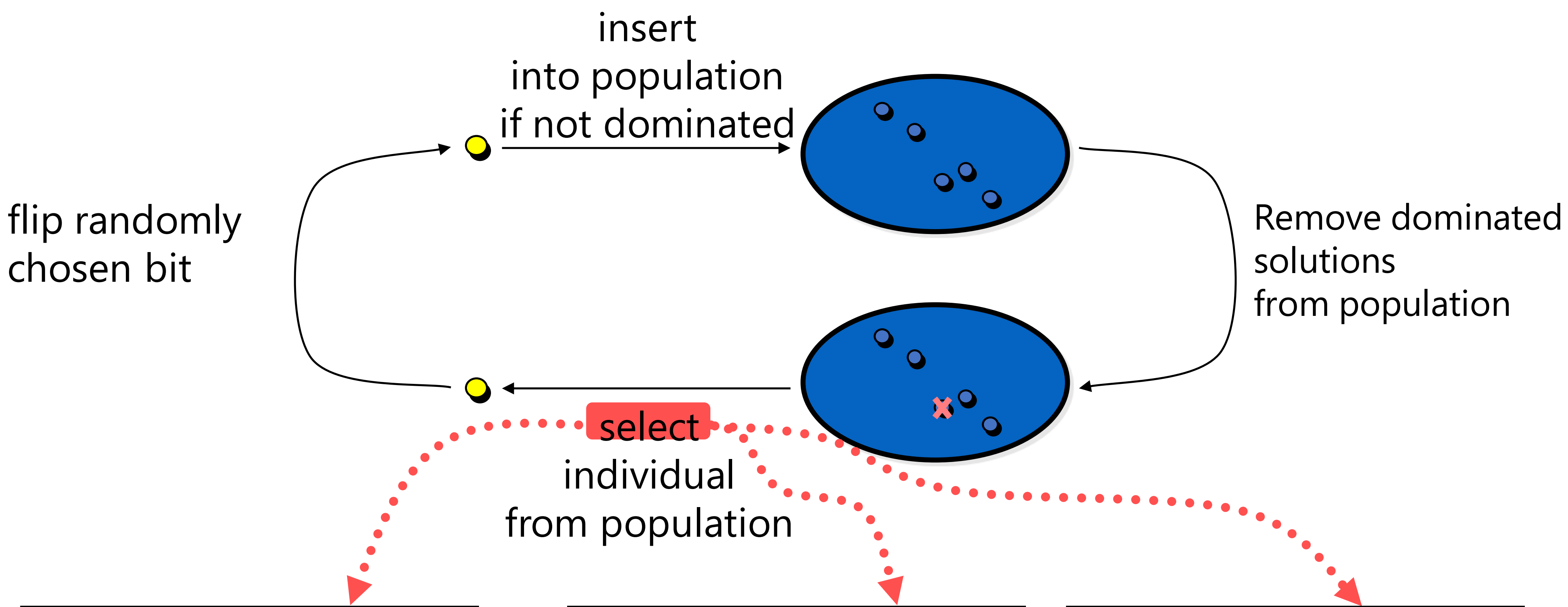
- An allocation is **Pareto Optimal** when no further Pareto Improvements can be made. This is often called a **Strong Pareto Optimum** (SPO).

- The non-dominated subset of the entire feasible search space S is the globally Pareto-optimal set



Source wikipedia

Simple Multiobjective EAs



SEMO

Each individual in the population is selected with the same probability (uniform selection)

FEMO

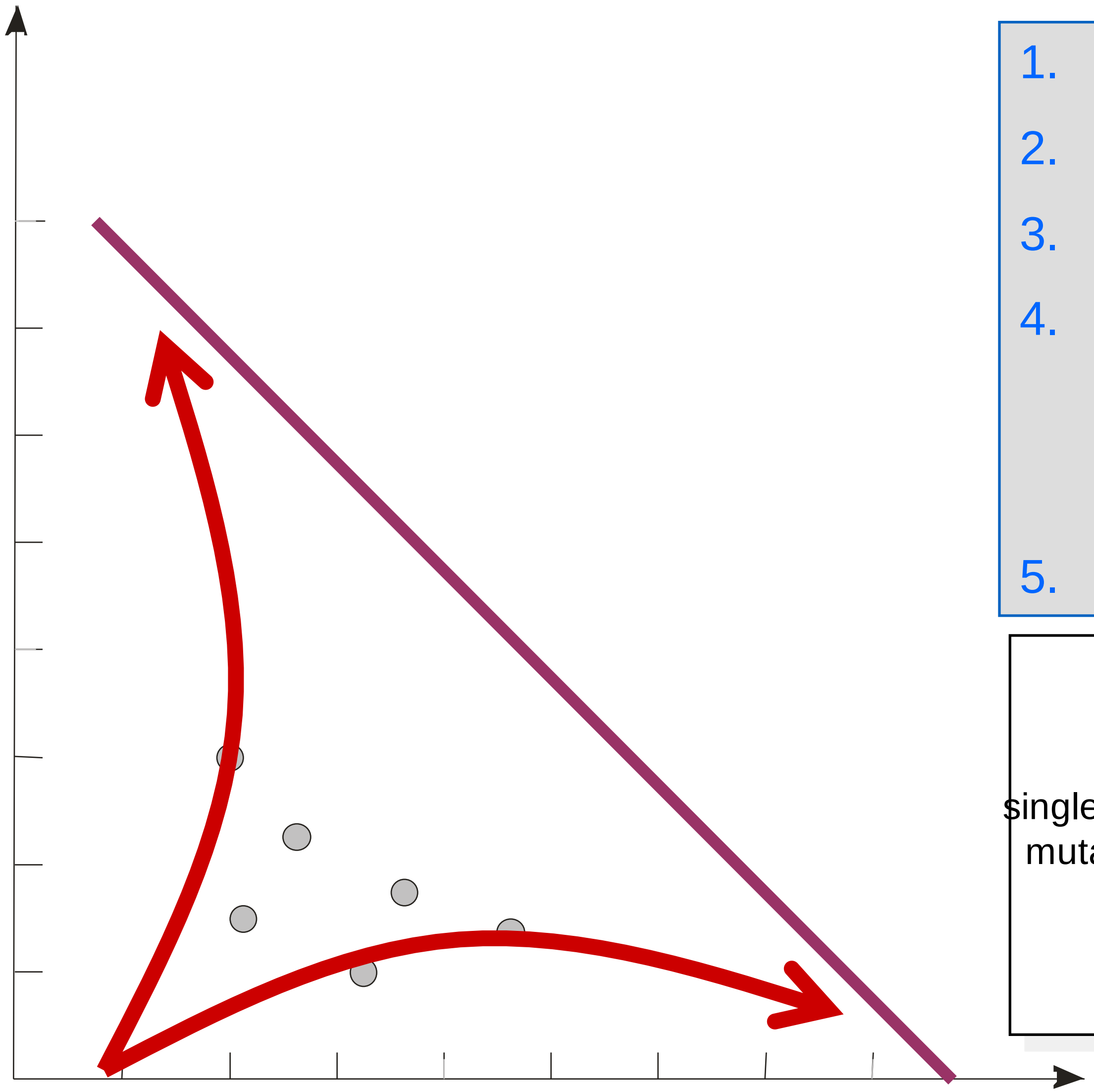
Select individual with minimum number of mutation trials (fair selection)

GEMO

Priority of convergence if there is progress (greedy selection)

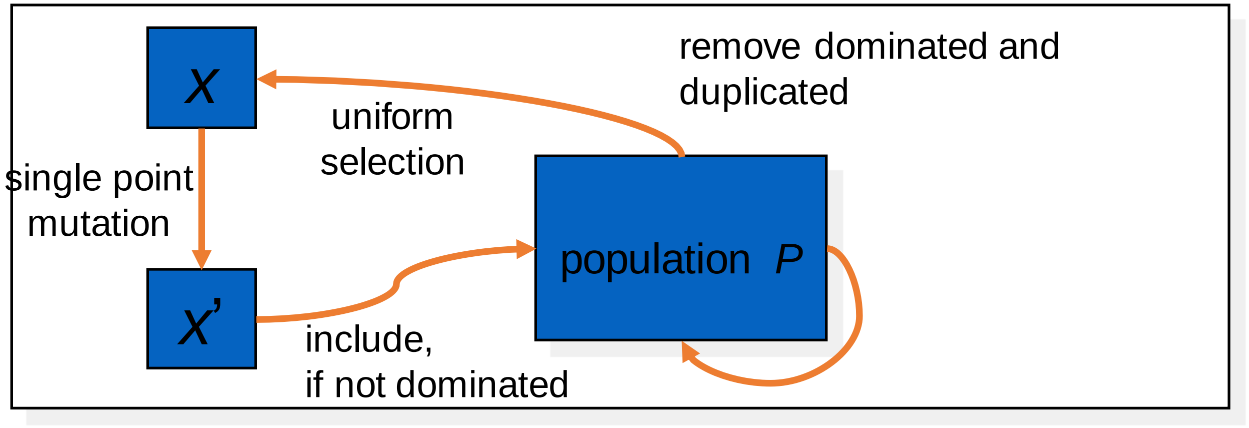
Inspired from tutorial' Eckart Zitzler on evolutionary optimization algorithms

Simple Evolutionary Multiobjective Optimizer



Inspired from tutorial' Eckart Zitzler on evolutionary optimization algorithms

1. Start with a random solution
2. Choose parent randomly (uniform)
3. Produce child by variating parent
4. If child is not dominated then
   - add to population
   - discard all dominated
5. Goto 2



Multi-Objective Optimization (EMOO) approaches state of the art

Non-Pareto Techniques

- Aggregating approaches
- VEGA (Vector Evaluated Genetic Algorithm)

Pareto Techniques

- Pure Pareto ranking
- NSGA (Non-dominated Sorted Genetic Algorithm-II, K. Deb) : diversity-preserving strategy via crowding…
- MOGA (Multi-Objective Genetic Algorithm)
- Ant-colony based

Recent Approaches

- PAES (The Pareto Archived Evolution Strategy, Kwnoles & Corne), maintains an archive population of non dominated solutions.
- SPEA (Strength Pareto Evolutionary Algorithm 2, Ziztler) use of an external population and clustering…

Bio-inspired Approaches

- PSO (particle swarm optimization)
- Ant-colony based

General idea: ensure a spread among the non dominated solutions while minimizing the distance to the optimal front

Pioneering techniques are around 15-20 years old, code sources of relevant techniques are available on the net

Evolutionary algorithms in practice

Evolutionary algorithms in practice

-Optimization problems: many uses in logistic (cf. Tsp problem..)

-Select a subset of features (remove irrelevant and redundant features…), instance (sampling).

-Generate parameters of a given algorithm (segmentation, clustering, Anns…)

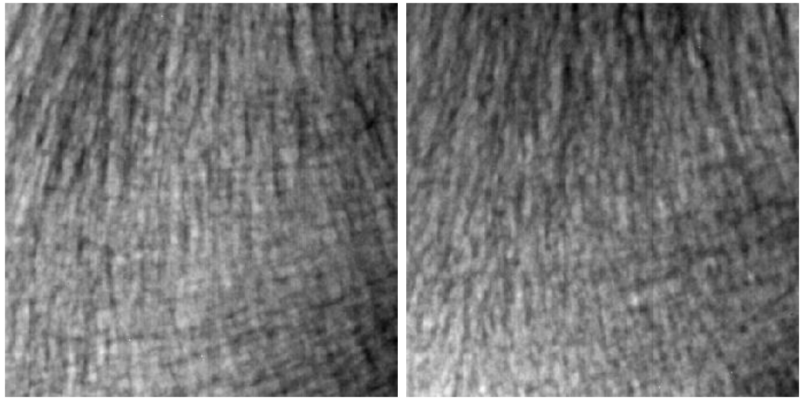
Domain fields: optimal control & design, finance, logistic, chemical engineering.. but relatively few in image (genetic & pso)!

	Evolutionary Algorithms	Ad-hoc Algorithms
Speed	Slow *	Generally fast
Human work	Minimal	Long and exhaustive
Applicability	General	There are problems that cannot be solved analytically
Performance	Excellent	Depends

Image discrimination using texture parameters

Classical uses: parameter selection & optimization

Classification of osteoporosis using X-ray images



OP patient normal subject

Objective: select texture parameters

Chromosome=[0,0,1,1,1..,0.2,..] => 2 parts, binary and continue

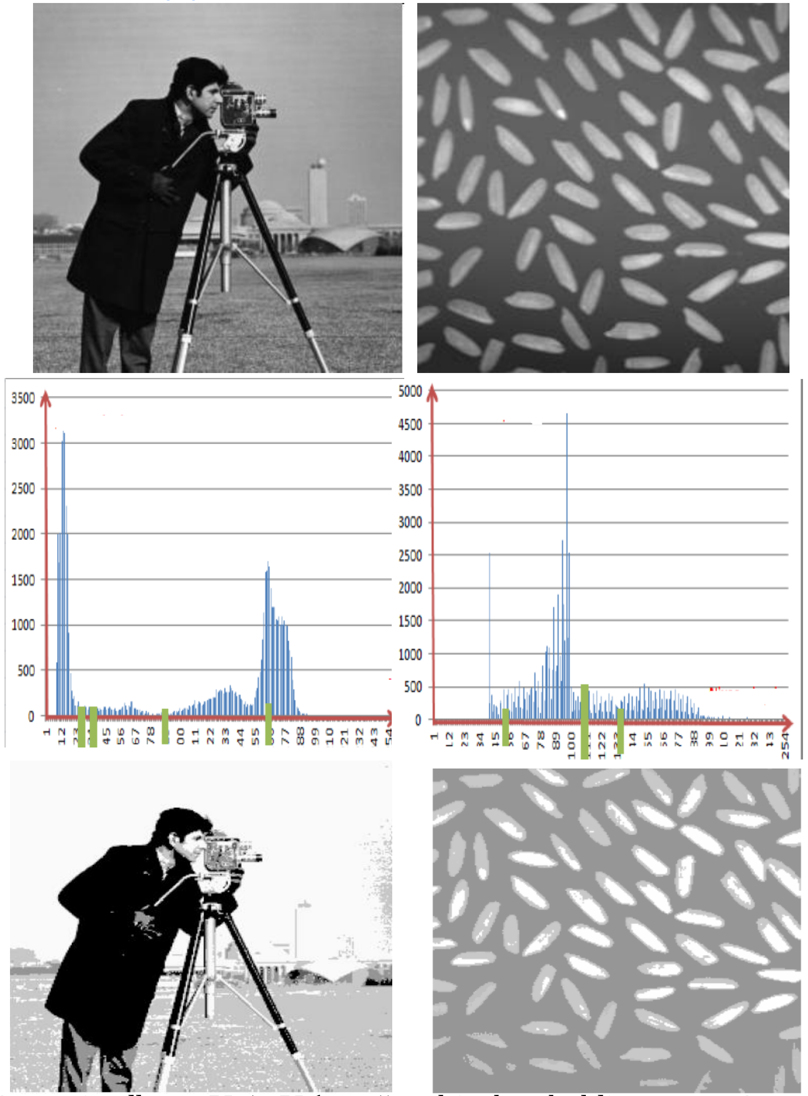
Fitness function= classifier(knn, anns, SVM…)

Result: rate > 10% on test (using a basic GA)

Yousfi, L., Houam, L., Boukrouche, A., Lespessailles, E., Ros, F., & Jennane, R. Texture Analysis and Genetic Algorithms for Osteoporosis Diagnosis. *International Journal of Pattern Recognition and Artificial Intelligence (2019)*.

Image tasks

Multi thesholding (direct application of Otsu approaches and derivates)



O. Banimelhem, Y. A. Yahya, “*Multi-Thresholding Image Segmentation Using Genetic Algorithm*”, IPCV, 2011

Noise reduction

Pick a window size of n×n
Use a real-valued chromosome of length n^2
Use a blending crossover
Use a modest mutation operator
Apply mask to noisy images
Set fitness to the Euclidean distance between original images and filtered noisy images

In this case, you get what you evolve for!

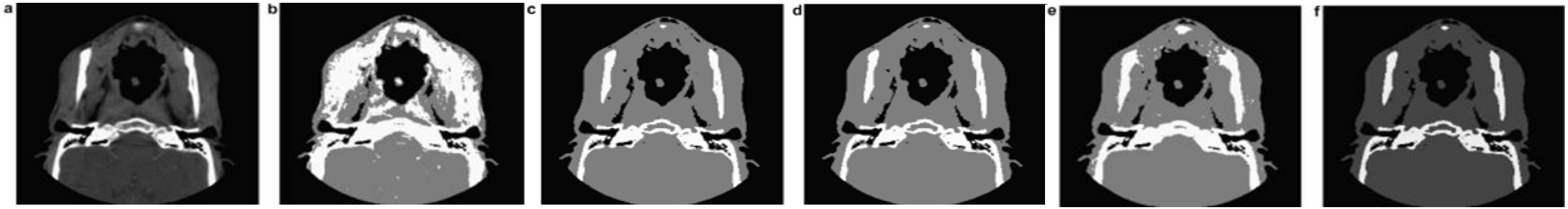
Clustering & genetic algorithms

Chromosome $[\overbrace{1\ 0\ 1\ 1\ 0}^{\text{control genes}}::\overbrace{53.2\ 19.6\ 34.7\ 68.2\ 75.3}^{\text{parametric genes}}]$

Fitness function $\min z = \sum_{i=1}^{k} \sum_{(x,y)\in R_i} [\,\mathrm{Rep}(R_i) - f(x,y)]^2$

Crossover: Uniform crossover

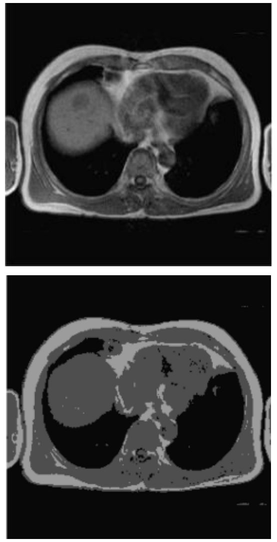
Mutation: bit flip and y'=y (1 +/- N(0,σ))



skull

	Actual pixels	D-thresholding		CHNN		k-Means		Fuzzy c-means		Via GA	
		Segmented pixels	Misclassified rate (%)	Segmented pixels	Misclassified rate (%)	Segmented pixels	Misclassified rate (%)	Segmented pixels	Misclassified rate (%)	Segmented pixels	Misclassified rate (%)
T5	3282	2106	35.83	2566	21.82	2594	20.96	2594	20.96	3290	0.24
T4	8745	9045	3.43	8810	0.70	8905	1.83	8872	1.45	8767	0.25
T3	9040	9004	0.40	9293	2.80	9158	1.31	9158	1.31	9029	0.12
T2	5590	7624	34.60	6631	18.62	6649	19.94	6732	20.43	5597	0.13
T1	38,879	37,857	2.6	38,236	1.65	38,230	1.67	38,180	1.8	38,853	0.06
Average error			15.38		9.13		8.94		9.19		0.16

Competitive hopfield neural network



Abdominal image

Chih-Chin Lai, Expert Systems with Applications 36 (2009) 248–259

Filter design (Finite impulse response)

Frequency space

Real Chromosome (vector, matrix of weights)

Find the components to match with the ideal frequential filter (MSE)

$$E = \sum_{i=1}^{m_1}\sum_{k=1}^{m_2}\left[D(\omega_{1j},\omega_{2k}) - F(\omega_{1j},\omega_{2k})\right]^2$$

D is the ideal frequency and F is the current response.

$$F(\omega_1,\omega_2) = \sum_{k_1=0}^{P_1}\sum_{k_2=0}^{P_2} a(k_1,k_2) * \cos(k_1\omega_1) * \cos(k_2\omega_2)$$

$a(k_1,k_2)$ is the matrix component. Filter of $N_1 x N_2$ dimensions.

$$P_1 = \frac{(N_1-1)}{2} \qquad P_2 = \frac{(N_2-1)}{2}$$

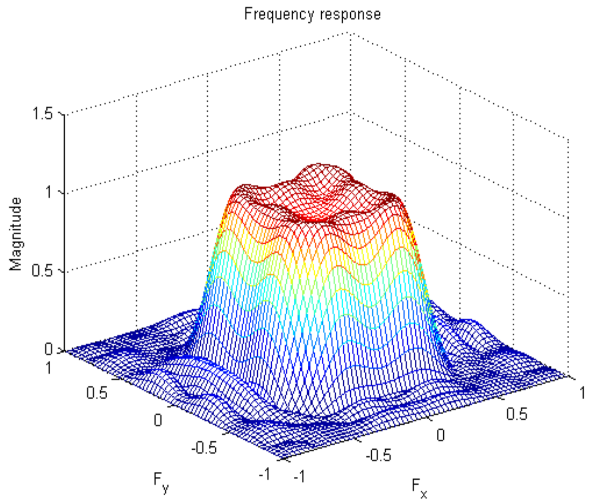
Fitness function: f = 1/(1+E)

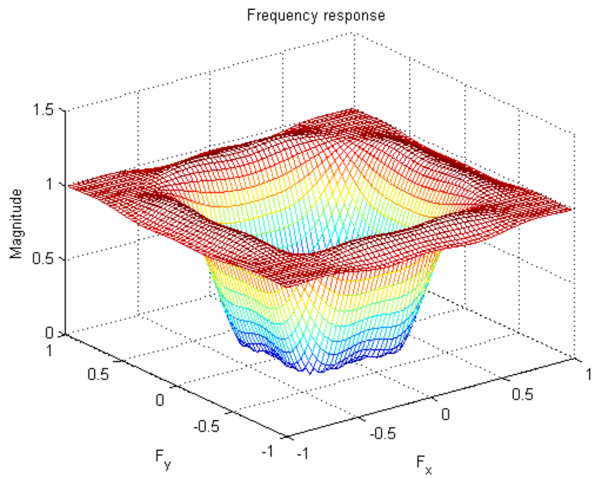
Crossover
$$\begin{cases} B_C^{Child1} = (B_i - B_j) * \lambda_{c1} + B_i \\ B_C^{Child2} = (B_j - B_i) * \lambda_{c2} + B_j \end{cases}$$

Adaptative mutation
$$P_{M_i} = \begin{cases} \frac{k_1 * (fit_{max} - fit_i)}{(fit_{max} - fit_{avg})} & fit_i \geqslant fit_{avg} \\ k_2 & fit_i < fit_{avg} \end{cases}$$

Level adapted

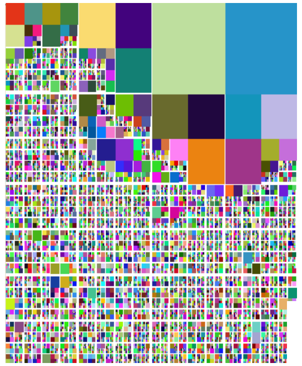
Mutation
$$B_M^{New} = B^{old} * (1 + \lambda_m)$$
where λ_m represents the level of modification and B defines each chromosome component.





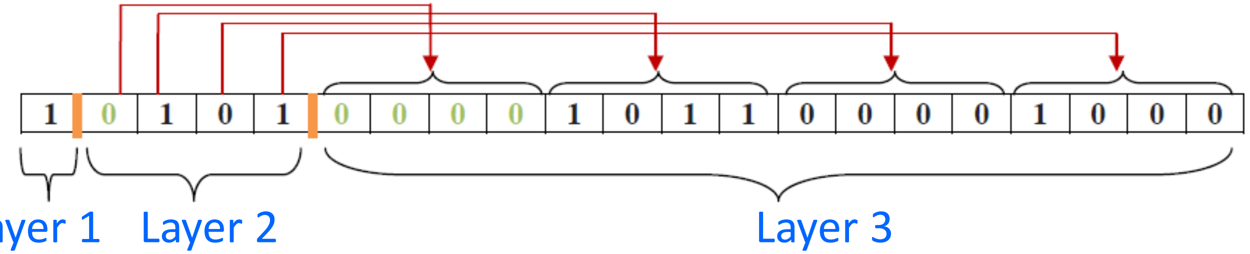
higher rate than conventional approaches but more computationnal

Boudjelaba. K, Ros F, ADAPTIVE GENETIC ALGORITHM FOR THE SYNTHESIS OF 2-D FIR FILTERS, IEEE signal processing conference, 2011.
Boudjelava K, Ros, F, Potential of swarm optimization and genetic algorithms for FIR filter design, Circuits syst signal processing, 2013



Other uses: quadtree

Chromosome

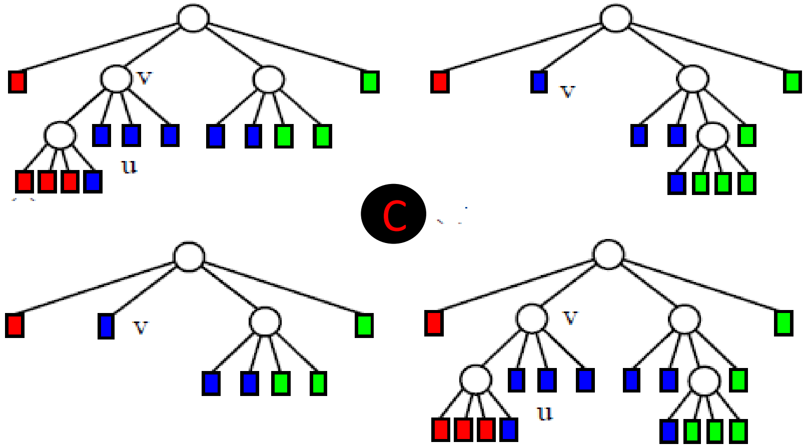


Fitness function $f = \lambda * \sum_{i=1}^{n} m_i *(255-\sigma_i)/\sum_{i=1}^{n} m_i + \mu * 255 * (1-(n/s))$

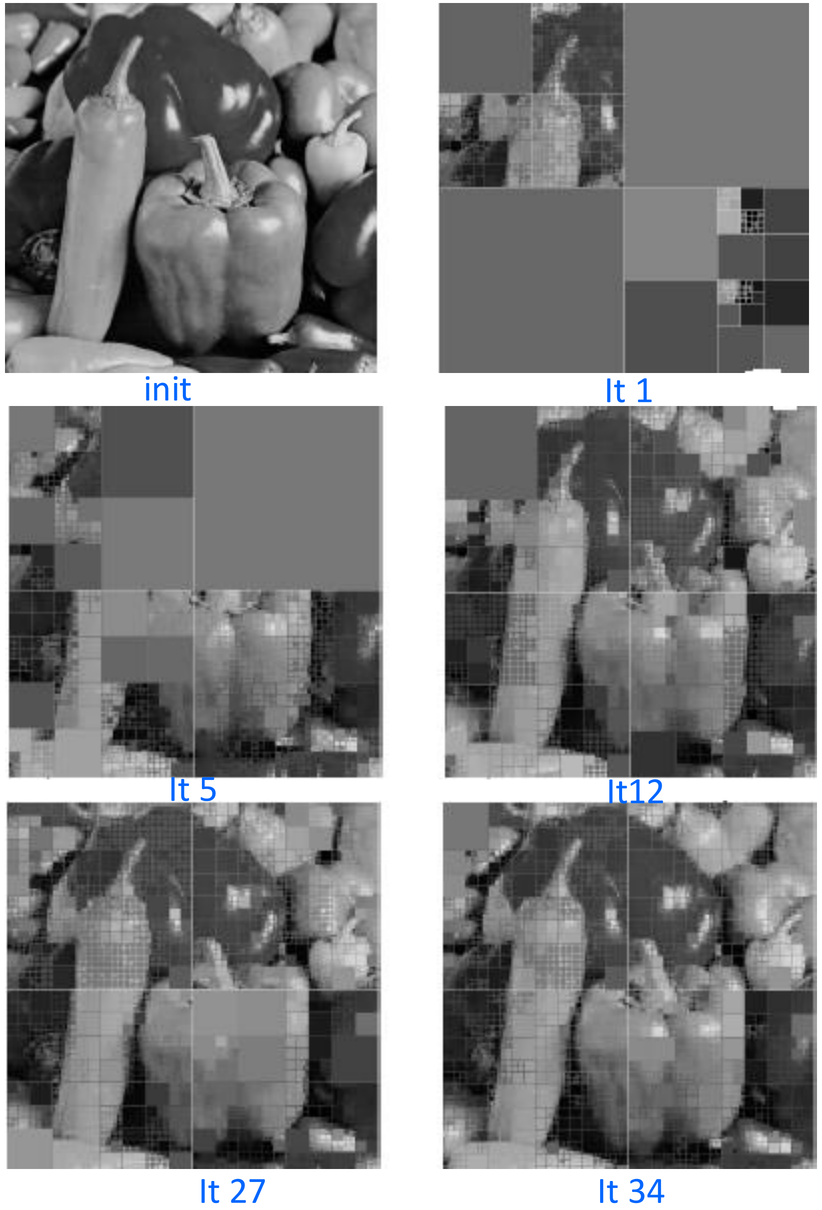
n (number of sub images), m_i & σ_i (statistics), s chrom size

λ, υ: parameters

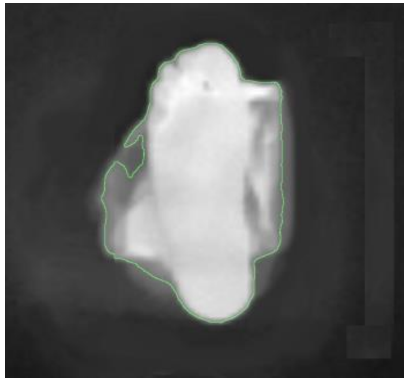
Crossover



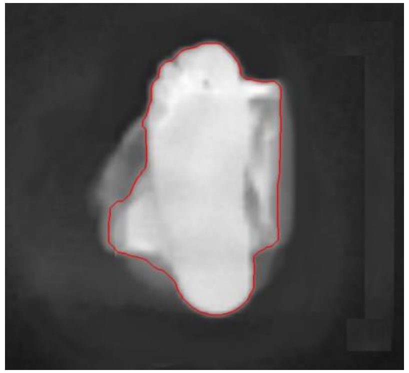
M. Gong, Y.-H. Yang / Pattern Recognition 37 (2004)



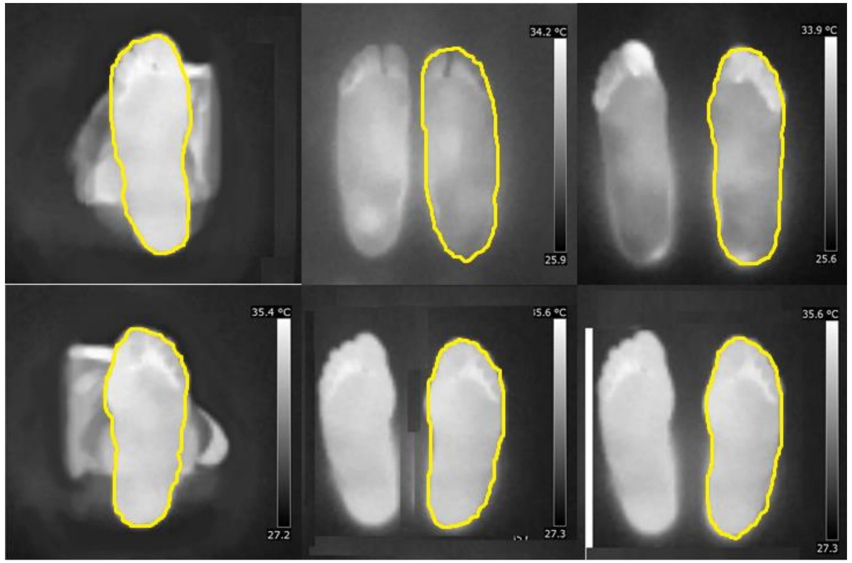
Segmentation with thermal images (active contours)



Chan et Vese



Branch and Mincut



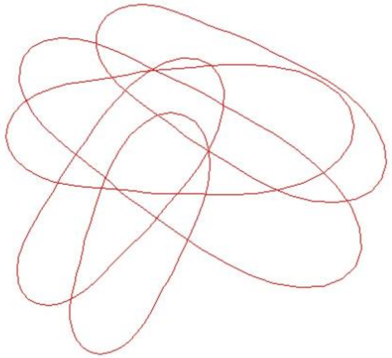
Hybrid HGA2

Objective: Segmentation

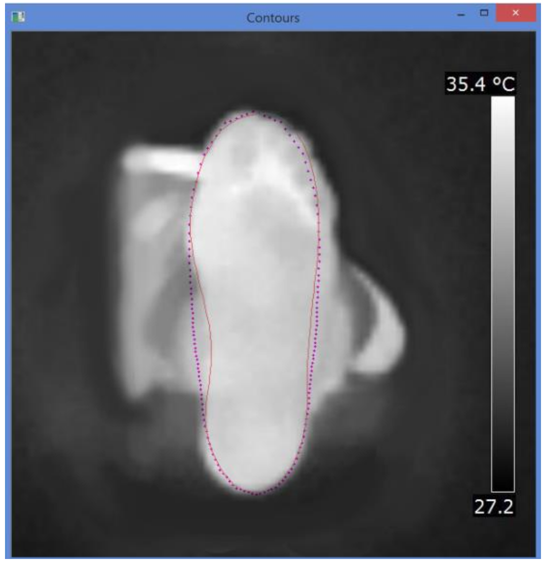
Chromosome= vector of discrete points from a Cassini model
Np+ 5 parameters: C_x, C_y, H_x, H_y, Teta (rst)

Fitness function= $ftn\text{ (i)} = \lambda_1 * \Delta_c + \lambda_2 * \Delta_r$ $\lambda_1 + \lambda_2 = 1$

Δ_c : contour information Δ_r : region information



Cassini model



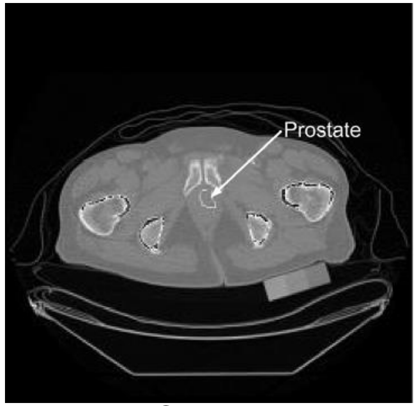
Hybrid model HGA2

Segmentation medical images

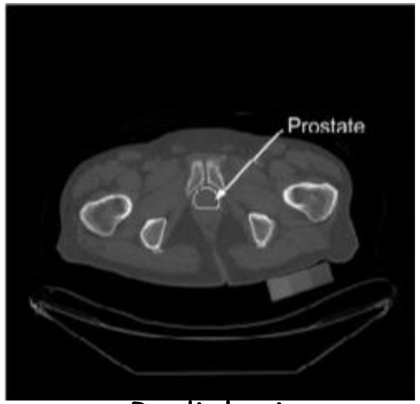
Active contours: prostate identification

- Ideal contours using a learning set of images
- Each contour has a unique shape and a pose (size, position and orientation).
- One modelises a medium shape and internal texture (including the variabilities).
- A population of chromosomes I(w,p) evolves until convergence (w: weight of the k textural descriptors, p: pose for the rst). The parameters w and p are generated in the possible space.
- The evaluation is done by matching the internal « texture » of each detected object with the medium « texture » found during the training phase.

Payel Gosh, Segmentation of medical images using genetic algorithms, 2006



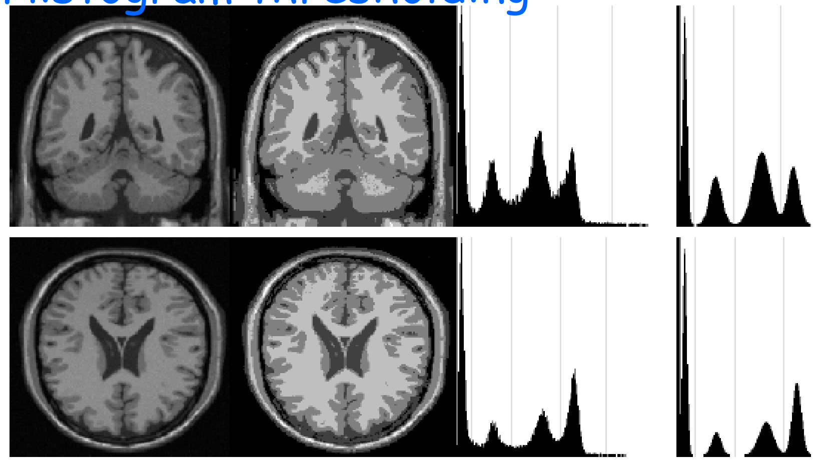
System



Radiologist

Classifier	*G*: Training Data	*G*: Test Data
GA	985	991
GENIE	950	708
Laws' Texture Measures	850	580

Histogram thresholding



PSO-2S Optimization Algorithm for Brain MRI Segmentation (Siarry 2013) sum of gaussian functions

Synthesis: art or science?

When to use EA?

- When space to be searched is large
- When the "best" solution is not necessarily required
- Approach to solving a problem not well-understood
- Problems with many parameters that need to be simultaneously optimized
- Problems that are difficult to describe mathematically

Drawbacks

- Difficult to find an encoding for the problem
- Difficult to define a valid fitness function
- May not return the global maximum, risk of premature convergence
- Exploration versus exploitation
- Can be time consuming.