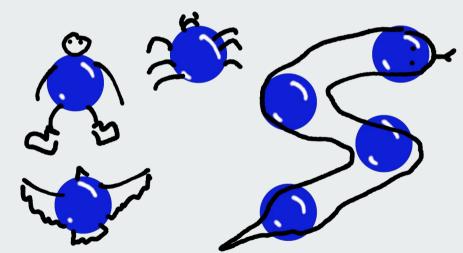
# Birds, hikers, snakes and ants

Bio-inspired optimisation algorithms



Reynolds, C. W. (1987). Flocks, Herds, and Schools: A Distributed Behavioral Model. In *Computer Graphics* (Vol. 21, Issue 4).

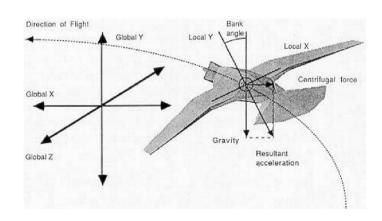
# Animals are particles with simple behaviours

Reynolds introduced "Boids", probably the first biological use of particles

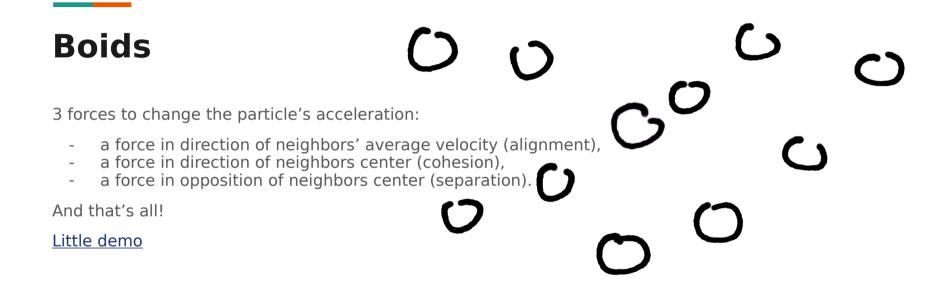
Boids are particles (3D points in R<sup>3</sup> space)

They follow a simple logic:

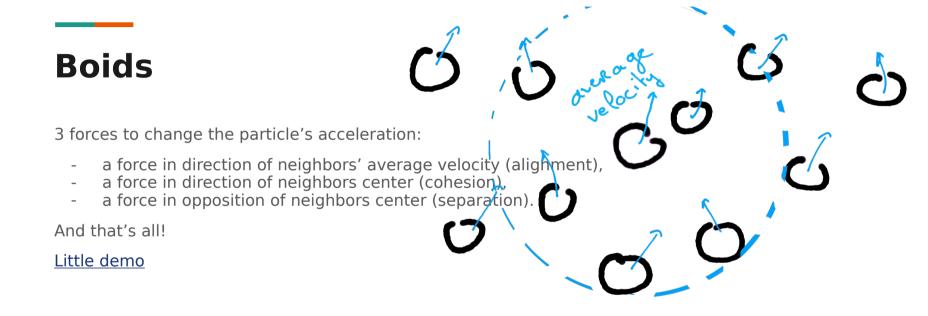
- Follow,
- Avoid,
- Group



Local behaviour = global pattern



Local behaviour = global pattern



Local behaviour = global pattern

# **Boids** 3 forces to change the particle's acceleration: a force in direction of neighbors' average velocity (alignment), a force in direction of neighbors center (cohesion), a force in opposition of neighbors center (separation). And that's all! Little demo

Local behaviour = global pattern

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Local behaviour = global pattern

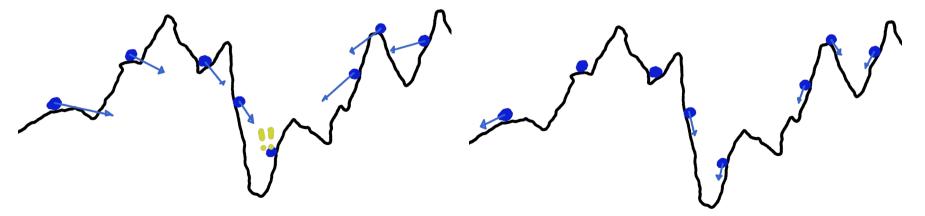
Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. *Proceedings of ICNN'95 - International Conference on Neural Networks*, *4*, 1942–1948.

# Social particles for optimisation

Particle Swarm Optimisation (PSO), a global minimum algorithm against Gradient Descent weaknesses.

No need for differentiation, no problem on non-differentiable function.

A single evaluation per step, even on N-dimensional spaces!



# **PSO** idea

## **Gradient Descent idea**

Algorithm: Algorithm:

Each particle has a position	Each particle has a position
Evaluate the function	Evaluate the function and the gradient
	- You probably want to compute the finite difference method to compute the slope in each direction independently
Keep track of the best evaluation made so far	
Move a little bit toward the group's best evaluation and your own best evaluation <u>Little demo</u>	Move in the direction of the gradient for an unknown distance
	- If the slope is null, you're dead - If there is a discontinuity, you're dead - If the slope is gentle, it's going to be a long ride Little demo

9

Cui, Z., & Shi, Z. (2009). Boid particle swarm optimisation. International Journal of Innovative Computing and Applications.

# Introduce neighborhood

Increase searching area by having interconnected subgroups: "neighborhoods"

Cui, Z., & Shi, Z. (2009). Boid particle swarm optimisation. International Journal of Innovative Computing and Applications.

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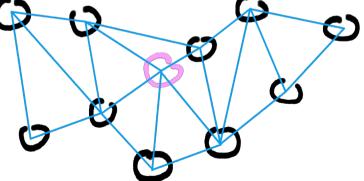
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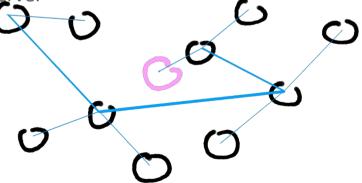
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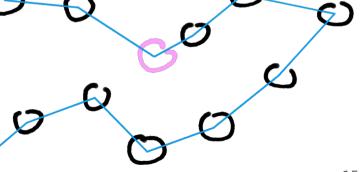
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# Introduce neighborhood

Increase searching area by having interconnected subgroups: "neighborhoods"



# Local constraints instead of global constraints

We've seen that particles can locally create a global behaviour,

We've seen that particles can locally find optimal minimisations,

We'll see that particles can do both at once.

### Algorithm:

- Each particle is linked by springs with 2 neighbors
- Each particle follow the gradient of a function.

The end.

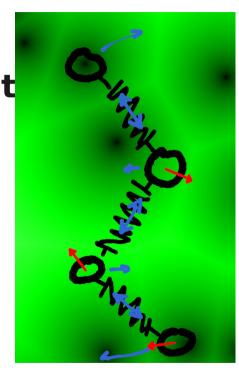
<u>Little demo</u>



### Algorithm:

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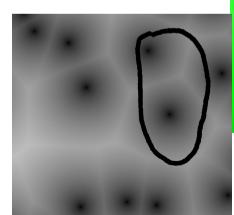
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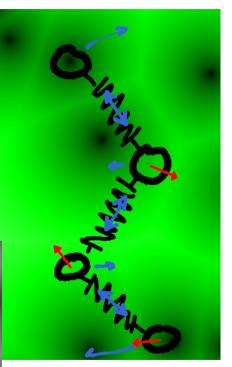


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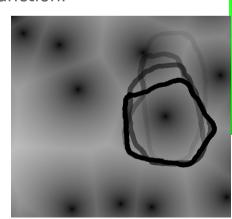




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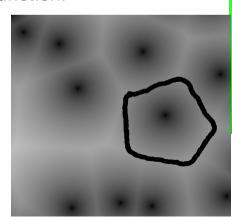


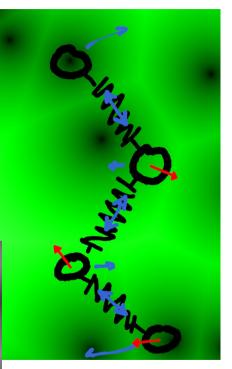


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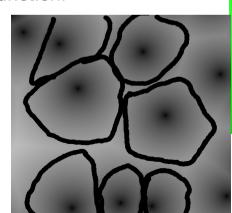


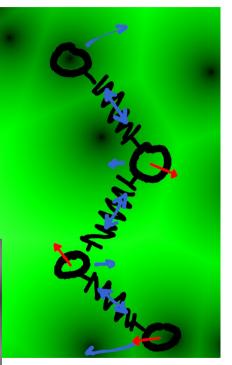


### Algorithm:

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# Snake, easy to compute

Minimisation of energy in a system

- Internal energy (controls locally the shape)
  - "Continuity"
  - "Curvature"
- External energy (controls the positioning of the shape, what we want to optimise)
  - "Image"

$$E_{\text{snake}}^* = \int_0^1 E_{\text{snake}}(\mathbf{v}(s)) ds$$
$$= \int_0^1 E_{\text{int}}(\mathbf{v}(s)) + E_{\text{image}}(\mathbf{v}(s))$$
$$+ E_{\text{con}}(\mathbf{v}(s)) ds$$

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Minimisation of energy in a system

- Internal energy (controls locally the shape)
  - "Continuity"
  - "Curvature"
- External energy (controls the positioning of the shape, what we want to optimise)
  - $E_{\text{snake}}^* = \int_0^1 E_{\text{snake}}(\mathbf{v}(s)) \, ds$

$$= \int_0^1 E_{\text{int}}(\mathbf{v}(s)) + E_{\text{image}}(\mathbf{v}(s))$$

 $E_{\text{image}} = w_{\text{line}} E_{\text{line}} + w_{\text{edge}} E_{\text{edge}} + w_{\text{term}} E_{\text{term}}$ 

$$\rightarrow$$
 +  $E_{con}(\mathbf{v}(s)) ds$ 

Minimisation of energy in a system

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$$= \int_0^1 E_{\text{int}}(\mathbf{v}(s)) + E_{\text{image}}(\mathbf{v}(s))$$

$$E_{\text{line}} = -(G_\sigma * \nabla^2 I)^2$$

 $=-|\nabla I(x,v)|$ 

 $E_{\text{int}} = (\alpha(s)|\mathbf{v}_{s}(s)|^{2} + \beta(s)|\mathbf{v}_{ss}(s)|^{2})/2$ 

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Minimisation of energy in a system

- "Continuity"
- "Curvature"

External energy (controls the positioning of the shape, what we want to optimise) 
$$E_{\text{image}}^* = \int_0^1 E_{\text{snake}}(\mathbf{v}(s)) \, ds \qquad \qquad E_{\text{image}} = w_{\text{line}} E_{\text{line}} + w_{\text{edge}} E_{\text{edge}} + w_{\text{term}} E_{\text{term}} = \int_0^1 E_{\text{int}}(\mathbf{v}(s)) + E_{\text{image}}(\mathbf{v}(s)) ds \qquad \qquad E_{\text{line}} = -(G_\sigma * \nabla^2 I)^2 = \frac{\partial^2 C}{\partial C} \frac{\partial n_\perp^2}{\partial C} ds$$

# Snake, awful to tune

Perfect when the "object" is at the center of the space.

Perfect when there is a "global gradient" towards the object.

Perfect when the initial curve is already in a "good initial position".

But what if...

- the gradient is null around a vertex,
- the slope is too gentle in the whole area,
- we don't have the good initial conditions,
- ...?

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Gunn, S. R., & Nixon, M. S. (1995). *Improving snake performance via a dual active contour* (pp. 600–605)

# **Snake, some improvements**

- Null gradient around the shape:
  - Force the contours to grow

- We don't know how to choose the initial conditions:
  - Use of dual-snakes

Gunn, S. R., & Nixon, M. S. (1995). *Improving snake performance via a dual active contour* (pp. 600–605)

# **Snake, some improvement**







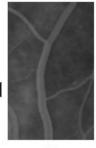


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# **Snake, some improvement**



(a)

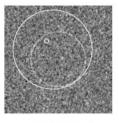


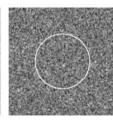


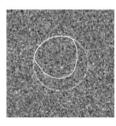


- Null gradient around the shape:
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(a) Example Initialisation

(b) Example Dual Result

(c) Example Kass result







(d) Cup Initialisation

(e) Dual Cup Result

(f) Kass Cup Result

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# **Snake, some improvement**

(a)

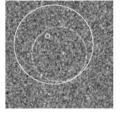


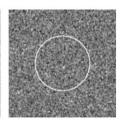


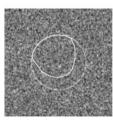


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(a) Example Initialisation

(b) Example Dual Result

(c) Example Kass result

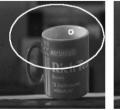
### Snakes: Active contour models

M Kass, A Witkin, D Terzopoulos - International journal of computer vision, 1988 - Springer

... Figure 5 shows an example of such a snake exposed to a standard subjective contour illusion

[7]. The shape of the snake contour between the edges and lines in the illusion is entirely ...

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# **Snake, my Todo list**

- Find a good initial curve placement using the Ant Colony Optimisation

- Mixing PSO and Snake for speeding up the convergence