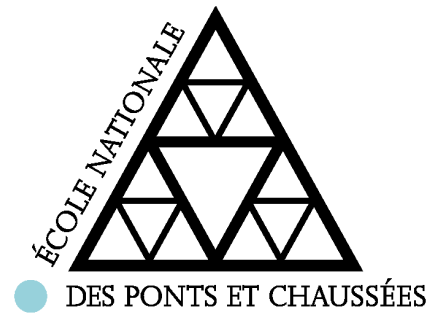


Shape Statistics



Aim : object classification or recognition, by building priors on the shape of the object, considering the information given by a sample set of different examples of this object.

Technical considerations

We use the Level-Set technique, ie we represent a curve by the zero-level of a function defined on the whole plane, and not by a list of points.

Curve Warping

Let A and B be two planar curves. We would like to warp continuously A to B .

Shape space, derivatives, Hausdorff distance

We consider the space \mathcal{X} of all curves A in $\mathcal{C}^2(\mathbb{S}_1, \mathbb{R}^2)$ such that $\|\partial_p A(p)\|$ does not vary with p .

Deformation fields for a given curve A : elementary deformations which one can apply to A .

\hookrightarrow fields δA in $\mathcal{C}^1(\mathbb{S}_1, \mathbb{R}^2)$, with the intuitive warping

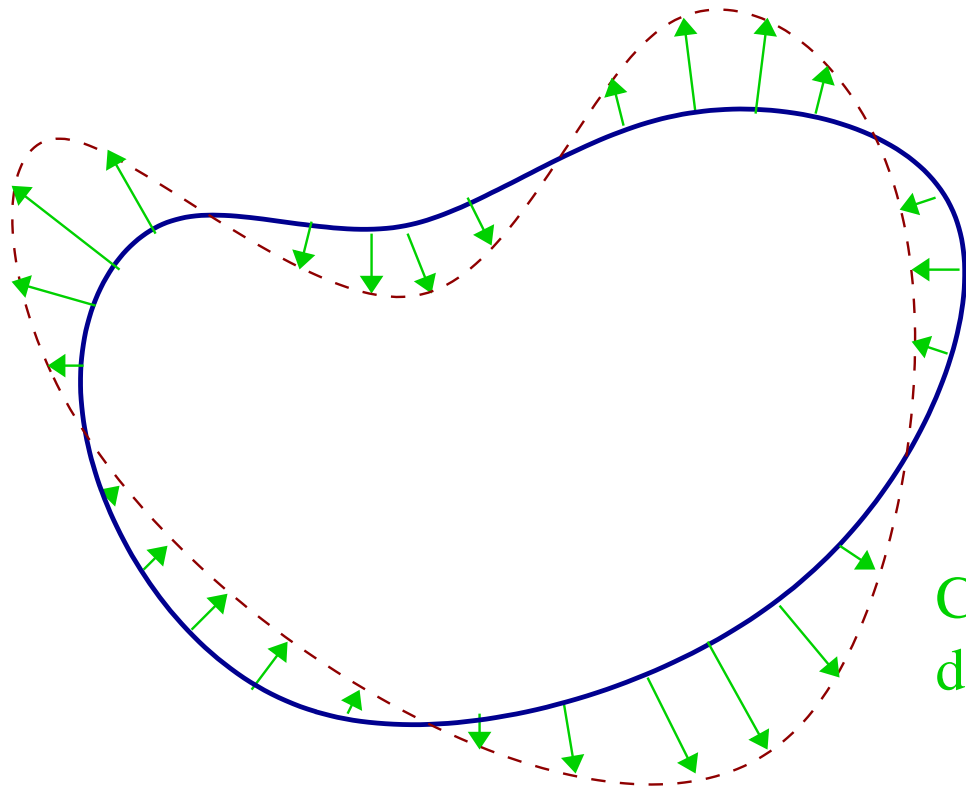
$$A(p) \mapsto A(p) + \delta A(p)$$

\hookrightarrow normal fields β in $\mathcal{C}^1(\mathbb{S}_1, \mathbb{R})$, with the warping

$$A(p) \mapsto A(p) + \beta(p) \vec{n}(p)$$

\hookrightarrow scalar product in the tangent space :

$$\langle \beta_1 | \beta_2 \rangle = \int_A \beta_1 \beta_2 d\sigma$$



Courbe A

Champ de déformation,
dans l'espace tangent de A

Natural distances

Natural “geodesic distance” :

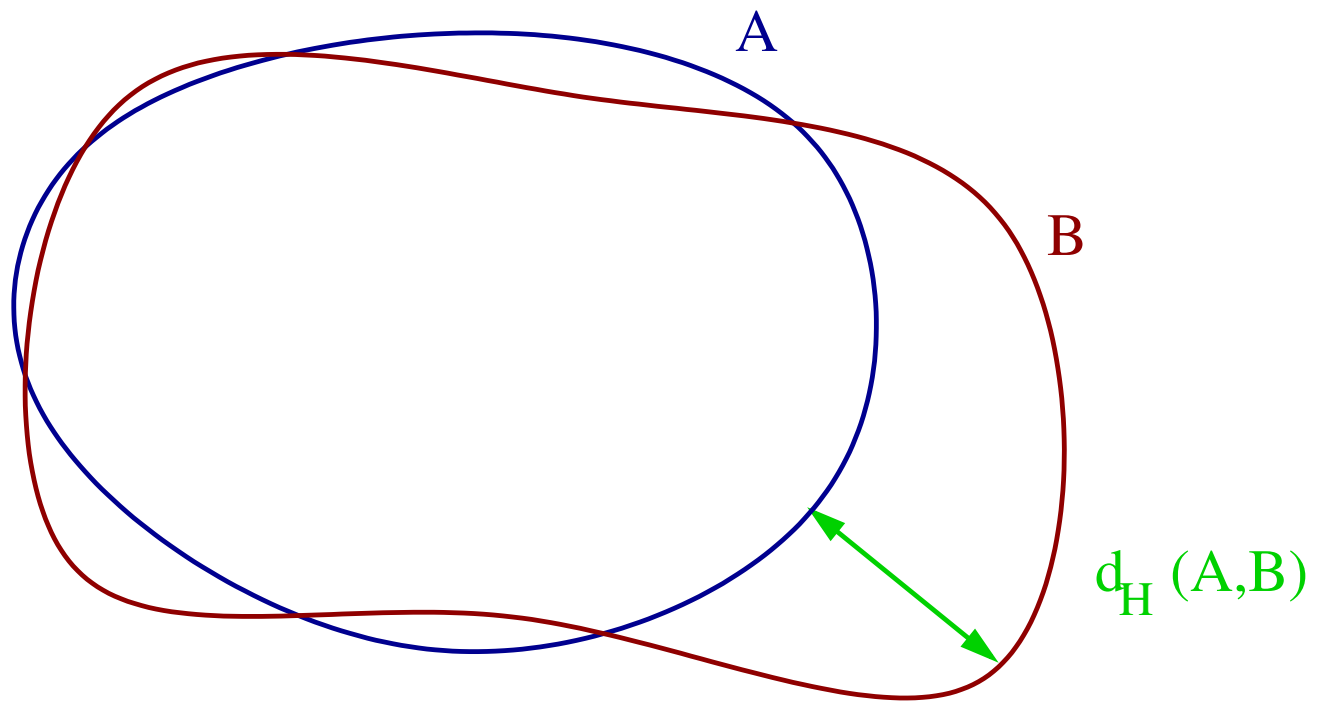
$$d_G(A, B) = \inf_{\Gamma \in \mathcal{F}(A, B)} \int_{\Gamma} \|\Gamma'(t)\| dt$$

where $\mathcal{F}(A, B)$ is the set of all paths in \mathcal{C}^1 going from A to B .

Hausdorff distance :

$$d_H(A, B) = \sup_{x \in A} d(x, B) + \sup_{y \in B} d(y, A)$$

Not derivable...



A

B

$d_H(A,B)$

Derivative of a function E with respect to a curve : linear function L such that, for all deformation field v :

$$Lv = \lim_{\varepsilon \rightarrow 0} \frac{1}{\varepsilon} (E(A + \varepsilon v) - E(A))$$

\hookrightarrow gradient : deformation field $\nabla E(A)$ satisfying, for all v ,

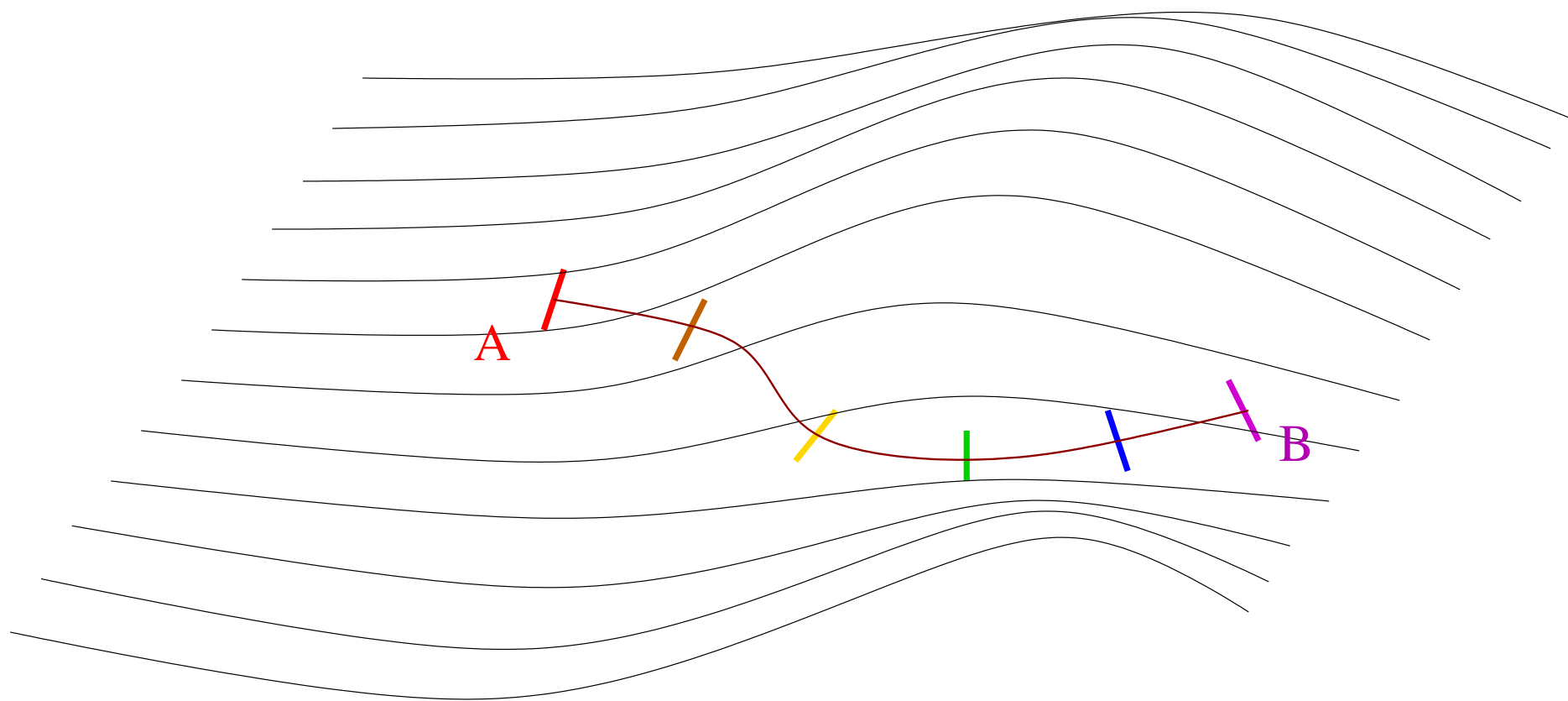
$$Lv = \langle \nabla E(A) | v \rangle$$

\hookrightarrow gradient descent on E :

$$\partial_t \mathcal{C} = \nabla E(\mathcal{C}(t))$$

or

$$\partial_t \mathcal{C} = \frac{\nabla E(\mathcal{C}(t))}{\|\nabla E(\mathcal{C}(t))\|}$$



Smoothing Hausdorff, Notations

We need a smooth function for a gradient descent, near from the Hausdorff distance.

Main idea : if f is a positive continuous function :

$$\lim_{\alpha \rightarrow \infty} \left(\int_A (f(y))^\alpha dy \right)^{1/\alpha} = \sup_{y \in A} f(y)$$

\hookrightarrow smooth approximation of \sup_A :

$$\left(\int_A (f(y))^\alpha dy \right)^{1/\alpha}$$

for any real α .

Notation for a mean quantity :

$$\langle f \rangle_A = \frac{1}{|A|} \int_A f$$

↪ For a suitable measurable injective function φ :

$$\langle f \rangle_A^\varphi = \varphi^{-1} \left(\frac{1}{|A|} \int_A \varphi \circ f \right)$$

↪ if Ψ grows quickly :

$$\langle f \rangle_A^\Psi \simeq \sup f$$

↪ if φ decreases quickly :

$$\langle f \rangle_A^\varphi \simeq \inf f$$

↪ approximation of the Hausdorff distance :

$$\max \left(\left\langle \left\langle d(\cdot, \cdot) \right\rangle_B^\varphi \right\rangle_A^\Psi, \left\langle \left\langle d(\cdot, \cdot) \right\rangle_A^\varphi \right\rangle_B^\Psi \right)$$

Particular case : approximation of the max of two numbers :

$$\langle a, b \rangle^\Psi = \Psi^{-1} \left(\frac{1}{2} \Psi(a) + \frac{1}{2} \Psi(b) \right)$$

↪

$$E_H(A, B) = \left\langle \left\langle \langle d(\cdot, \cdot) \rangle_B^\varphi \right\rangle_A^\psi, \left\langle \langle d(\cdot, \cdot) \rangle_A^\varphi \right\rangle_B^\psi \right\rangle^\Psi$$

↪ Max of two lengths :

$$E_L(A, B) = \langle |A|, |B| \rangle^\Psi$$

↪ Hybrid energy :

$$E_M = \langle E_H, \eta E_L \rangle^\Phi$$

where η is the ratio of the characteristic lengths in the problem (distance between curves, length difference).

Problems with E_H :

↪ not a distance on the space of curves \mathcal{X} ,

↪ $\forall A \in \mathcal{X}, E_H(A, A) \neq 0$,

↪ two curves A and B may satisfy $E_H(A, A) > E_H(A, B)$,

↪ a gradient descent with respect to C on $E_H(C, B)$ from A does not necessarily end at $C = B$,

↪ a gradient descent from B to A does not follow the same path as the one from A to B .

But : E_H is near from d_H : for a suitable choice of functions ψ , Ψ and Φ , we have, for all curves A and B in \mathcal{X} :

$$d_H(A, B) - \left(\alpha_\Psi + \alpha_\psi + \Delta_\Phi \frac{|A| + |B|}{2} \right)$$

$$\leq$$

$$E_H(A, B)$$

$$\leq$$

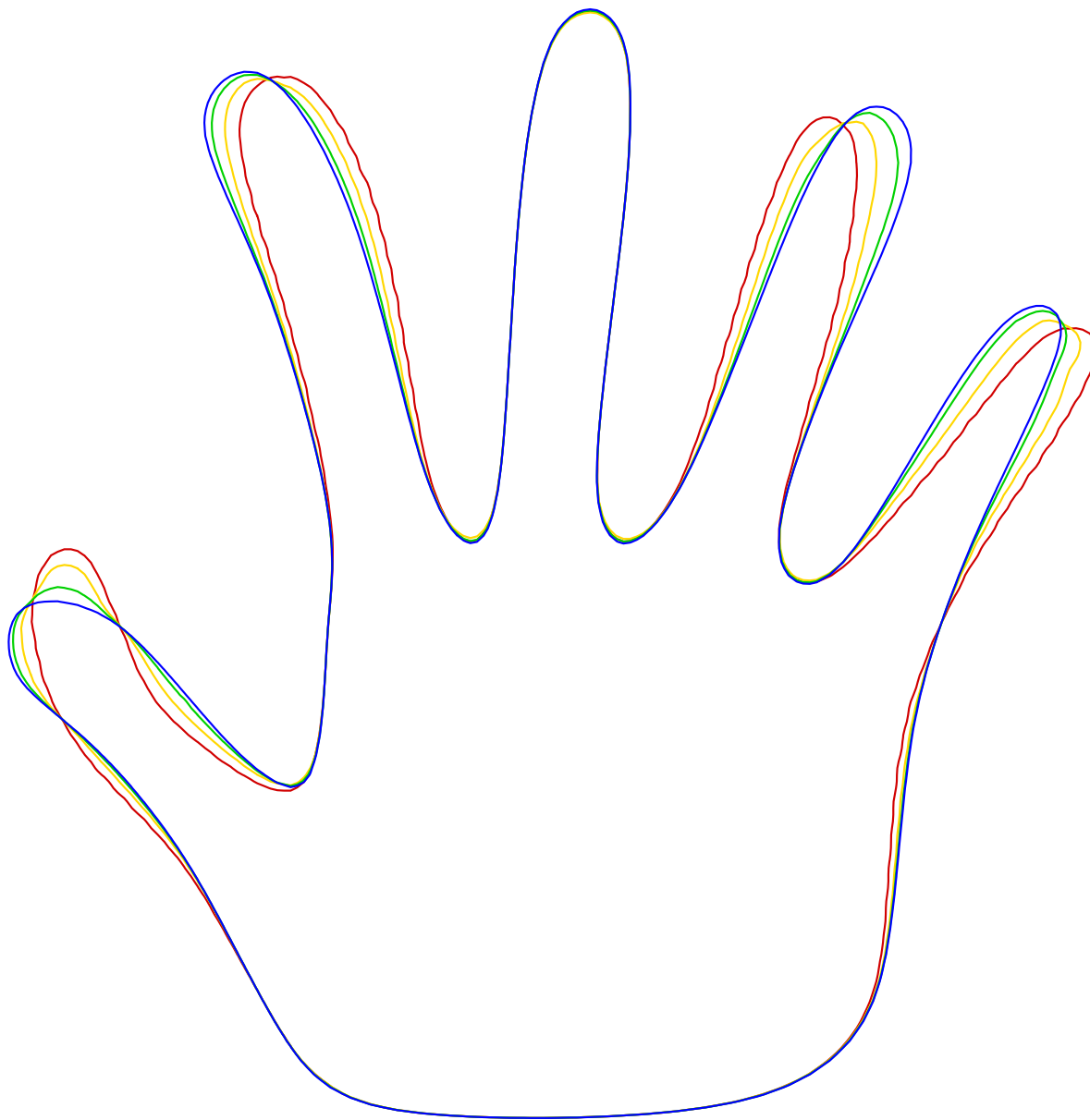
$$d_H(A, B) + \left(\alpha_\Phi + \Delta_\Psi \frac{|A| + |B|}{2} \right)$$

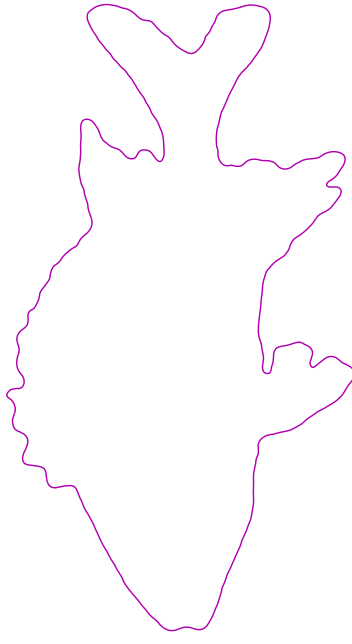
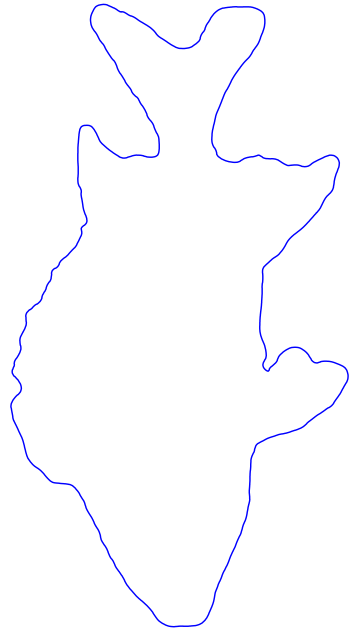
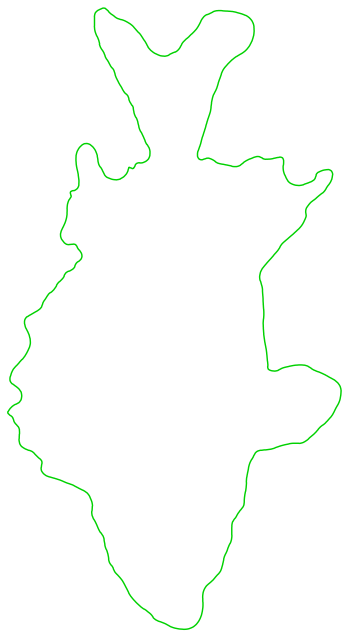
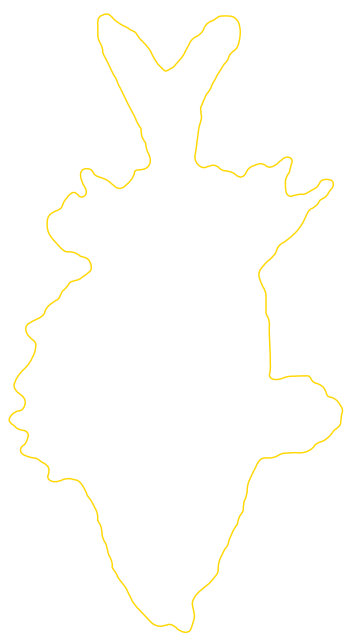
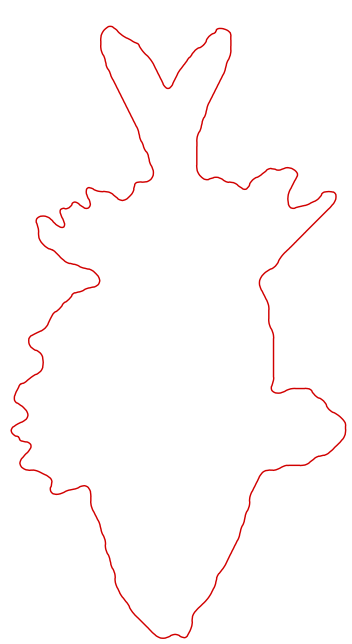
where α_Ψ , α_ψ and Δ_Φ are constants.

Examples

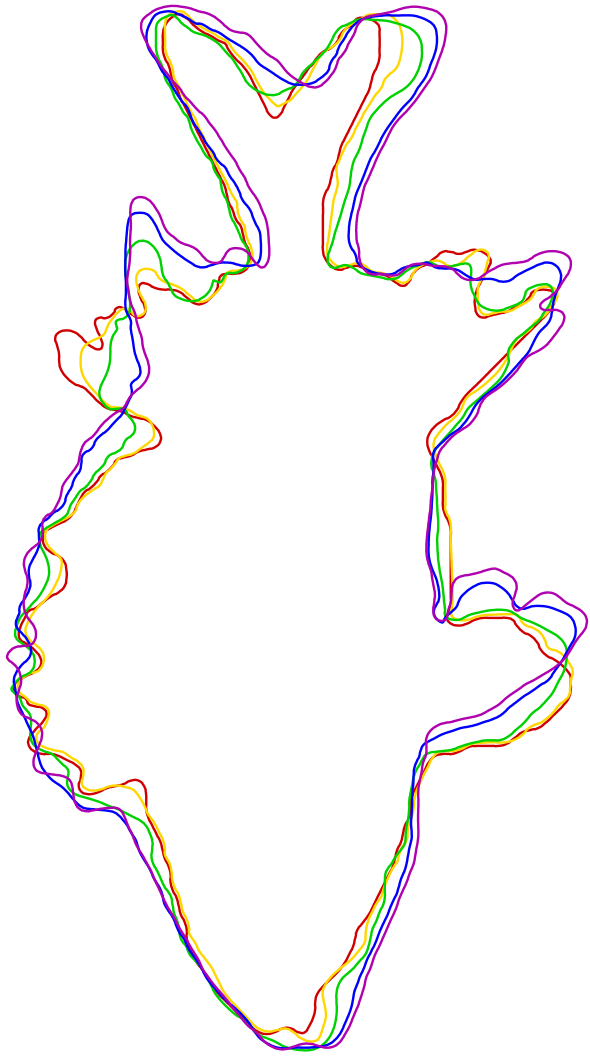
We consider for increasing functions some of the kind $x \mapsto x^\alpha$ and for the decreasing ones $(x + \varepsilon)^{-\alpha}$.

\hookrightarrow we choose α near 4...









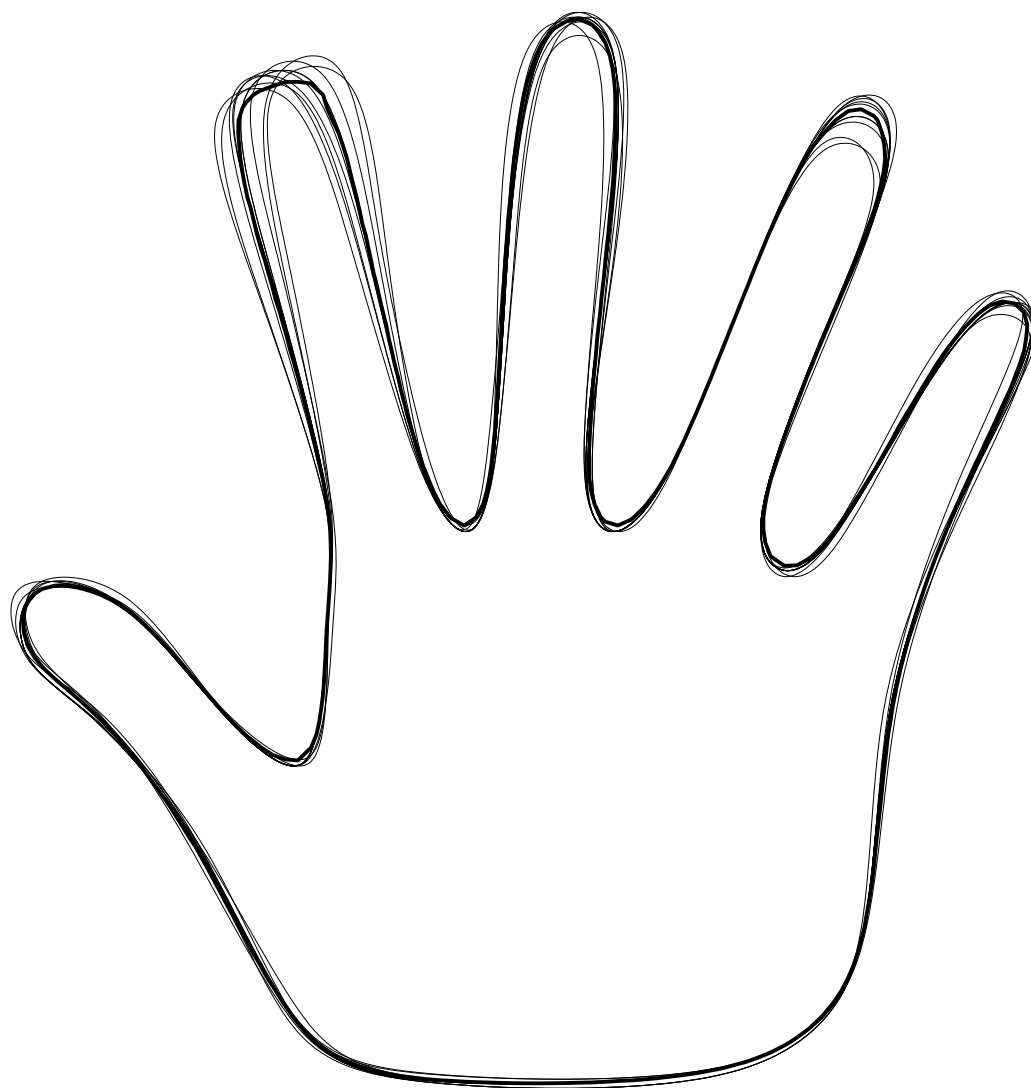
Mean of Curves, Characteristical Deformations

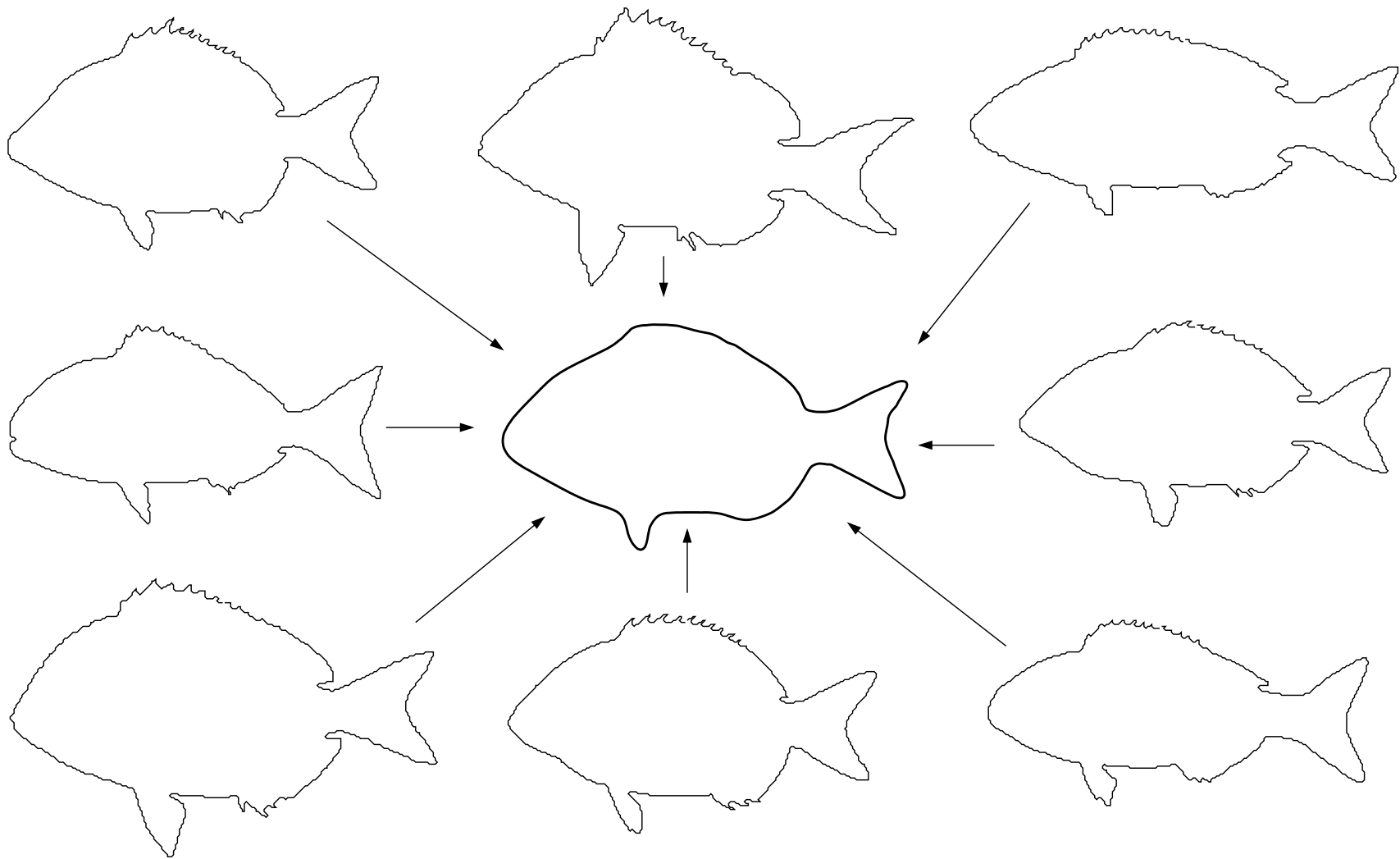
We consider n curves A_i , and search for their mean M :

↪ minimize $\sum_i E(M, A_i)^\alpha$, where $\alpha = 1$ or 2 ,

↪ we hope there will not be too many local minima.

↪ in practice, it works for reasonable cases.





We consider the curves A_i and their mean, M . We would like to define and compute their « characteristical deformations », ie some kind of “standard deviation” but defined for curves.

We note $\delta_i = \nabla_M E(M, A_i)^2$

We build the correlation matrix :

$$\Delta_{i,j} = \langle \delta_i | \delta_j \rangle$$

and in diagonalizing it, we obtain from the eigenvectors linear combinations of the deformations, hence characteristical deformations β_k .



Standard application : segmentation with priors.

↪ knowledge of a mean shape and of the characteristic allowed deformations

Other application : notion of similarity.

We keep the m first modes of deformation. For any curve Y , its distance to the set (curve M + deformations β_k) can be :

$$\sum_{k \leq m} \frac{\langle \nabla_M E(M, Y)^2 | \beta_k \rangle^2}{\sigma_k^2} + \frac{\|R(\nabla_M E(M, Y)^2)\|^2}{\sigma_R^2}$$

where

$$R(\beta) = \beta - \sum_{k \leq m} \langle \beta | \beta_k \rangle \beta_k$$

and

$$\sigma_R^2 = \frac{1}{|\mathcal{H}|} \sum_{C \in \mathcal{H}} \|R(C)\|^2$$