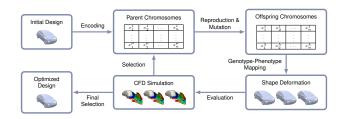
A Comprehensive Comparison of Shape Deformation Methods in Evolutionary Design Optimization



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²Honda Besearch Institute







Outline

- 1. Shape deformation methods
- 2. Evolutionary design optimization
- 3. Application: Passenger car design optimization

Fundamental requirements?

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- Different representations
 - Surface meshes
 - Volume meshes



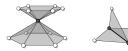


- Fundamental requirements?
- Different representations
 - Surface meshes
 - Volume meshes
- Defects
 - Badly shaped elements
 - Non-manifold meshes
 - Self-intersections













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 - Self-intersections
- → Space deformations



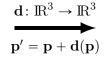






- Deformation function $\mathbf{d} \colon \mathbb{R}^3 \to \mathbb{R}^3$
- Warp embedding space around object \mathcal{M}









- Deformation function $\mathbf{d} \colon \mathbb{R}^3 \to \mathbb{R}^3$
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- Methods:
 - Free-form deformation (FFD)
 - Direct manipulation FFD
 - Radial basis functions



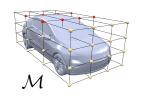
$$\mathbf{d} \colon \mathbb{R}^3 \to \mathbb{R}^3$$
$$\mathbf{p}' = \mathbf{p} + \mathbf{d}(\mathbf{p})$$



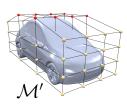
Free-Form Deformation

Free-Form Deformation (FFD)

- Embed object in control lattice
- Compute local coordinates
- Move control points
- Deform object according to updated control points

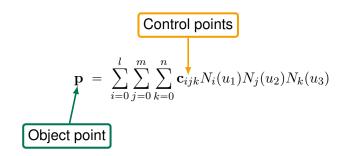


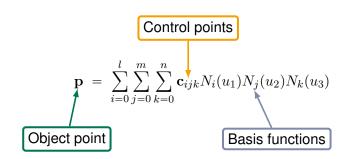
$$\mathbf{d}_{ffd} \colon \mathbb{R}^3 \to \mathbb{R}^3$$
$$\mathbf{p}' = \mathbf{p} + \mathbf{d}_{ffd}(\mathbf{u})$$

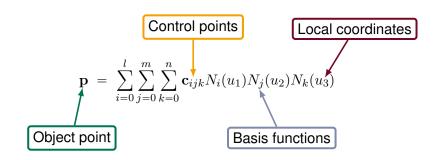


$$\mathbf{p} = \sum_{i=0}^{l} \sum_{j=0}^{m} \sum_{k=0}^{n} \mathbf{c}_{ijk} N_i(u_1) N_j(u_2) N_k(u_3)$$

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 Object point

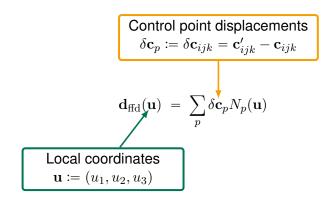




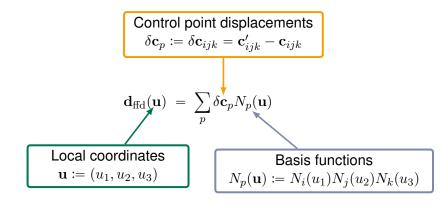


$$\mathbf{d}_{\mathrm{ffd}}(\mathbf{u}) \ = \ \sum_{p} \delta \mathbf{c}_{p} N_{p}(\mathbf{u})$$

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 Local coordinates
$$\mathbf{u} := (u_1, u_2, u_3)$$



S



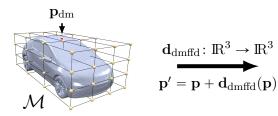
Free-Form Deformation: Caveats

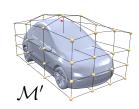
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Free-Form Deformation: Caveats

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- · Move object points directly
- Automatically compute control point displacements satisfying new object point locations





Solve linear system to compute control point displacements:

$$\begin{bmatrix} N_1(\mathbf{u}_1) & \dots & N_n(\mathbf{u}_1) \\ \vdots & \ddots & \vdots \\ N_1(\mathbf{u}_m) & \dots & N_n(\mathbf{u}_m) \end{bmatrix} \begin{pmatrix} \delta \mathbf{c}_1^T \\ \vdots \\ \delta \mathbf{c}_n^T \end{pmatrix} = \begin{pmatrix} \bar{\mathbf{d}}_1^T \\ \vdots \\ \bar{\mathbf{d}}_m^T \end{pmatrix}.$$

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- Not necessarily physically plausible
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Radial Basis Function

Deformation

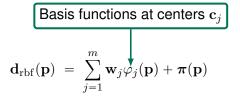
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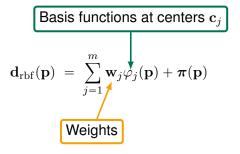
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$$\mathbf{d}_{\mathrm{rbf}}(\mathbf{p}) = \sum_{j=1}^{m} \mathbf{w}_{j} \varphi_{j}(\mathbf{p}) + \boldsymbol{\pi}(\mathbf{p})$$

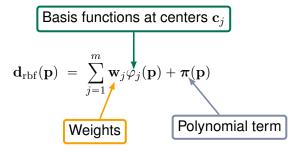
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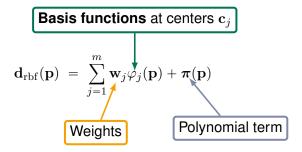
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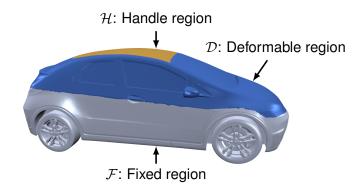
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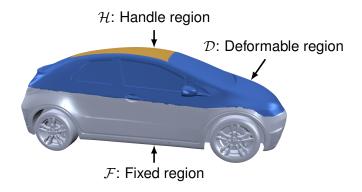
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Where to place kernels?

Handle-based direct manipulation interface



- Handle-based direct manipulation interface
- → Place kernels in handle and fixed regions

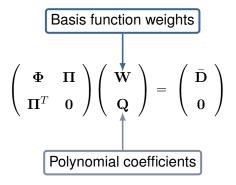


Determine weights and polynomial coefficients

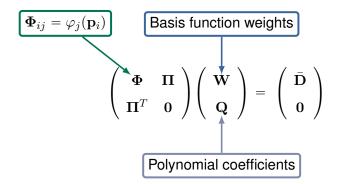
- Determine weights and polynomial coefficients
- → Solve linear system

$$\left(egin{array}{cc} oldsymbol{\Phi} & oldsymbol{\Pi} \ oldsymbol{\Pi}^T & oldsymbol{0} \end{array}
ight) \left(egin{array}{cc} oldsymbol{W} \ oldsymbol{Q} \end{array}
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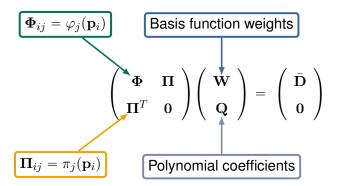
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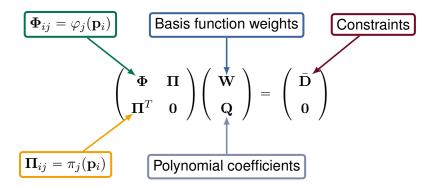
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RBF Deformation

- Smooth and physically plausible
- Satisfies constraints exactly
- No control lattice, flexible setup



$$\mathbf{d}_{\mathrm{rbf}} \colon \mathbb{R}^3 \to \mathbb{R}^3$$

$$\mathbf{p}' = \mathbf{p} + \mathbf{d}_{\mathrm{rbf}}(\mathbf{p})$$



Frank attaces

Evolutionary

Design Optimization

Evolutionary Algorithms

- Global optimization
- + Generate novel designs
- + Robustness to noise
- + Non-smooth, multi-objective target functions

Evolutionary Algorithms

- Global optimization
- + Generate novel designs
- + Robustness to noise
- + Non-smooth, multi-objective target functions
- Computationally expensive

Evolution Strategies (ES)

- Represent solutions as vectors of real numbers
- Create offspring by adding zero mean random vector
- Advantages:
 - Self-adaptation of strategy parameters during optimization
 - Simple incorporation of constraints

Covariance Matrix Adaptation ES

- Adapt covariance matrix to previously successful solutions
- + Fast convergence on small population sizes







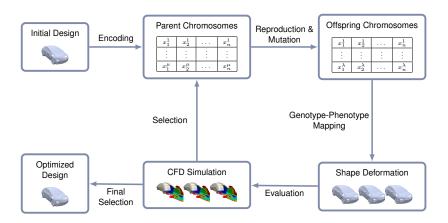


Passenger Car

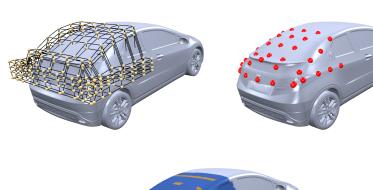
Design Optimization

Passenger Car Design Optimization

Goal: Improve aerodynamic drag of a simplified Honda Civic



Deformation Setups





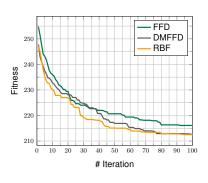
Fitness Function Evaluation

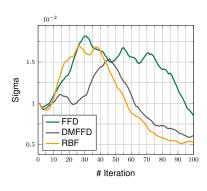
• Fitness function $f: \mathbb{R}^2 \to \mathbb{R}$:

$$f(\mathbf{x}) = w_1 v_1 + w_2 v_2.$$

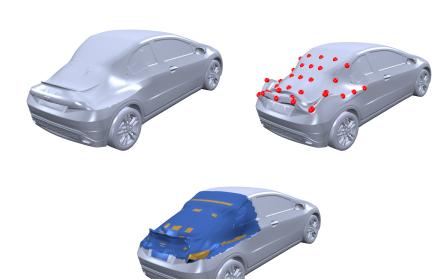
- v_1 : aerodynamic drag computed by CFD simulation
- v_2 : volume weight to penalize overly flat shapes

Results





Results



Conclusions & Future Work

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 - Strong coupling is important

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- Conclusions:
 - RBFs: Flexible setup with equivalent or better results
 - Strong coupling is important
- Future work:
 - Additional methods
 - Unified interface
 - Synthetic benchmarks

Thanks

... for your attention.

Questions?