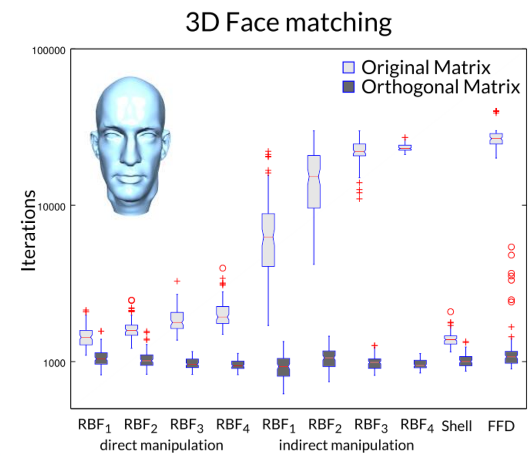
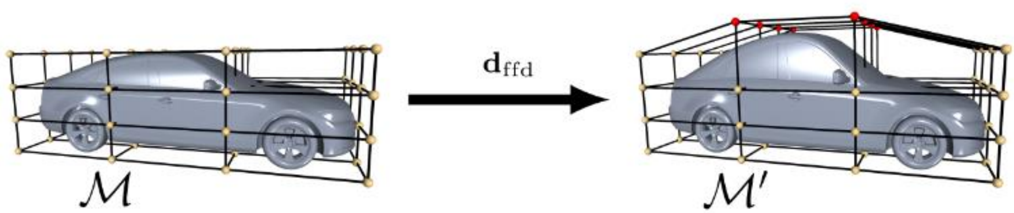
Honda Research Institute **EU**

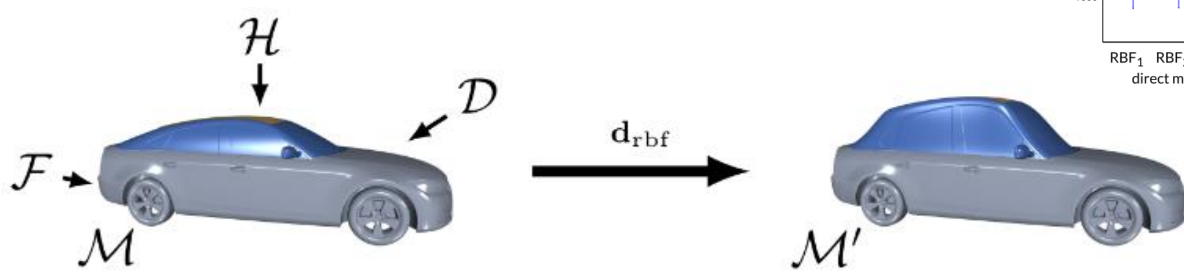
Structuring the Space of Opportunities

Representations in Evolutionary Design Optimization

Stefan Menzel, Honda Research Institute Europe, Offenbach, Germany







SAINT Workshop on Evolutionary Computation and Its Applications
March 25-26, 2019
SUSTech, Shenzhen, China

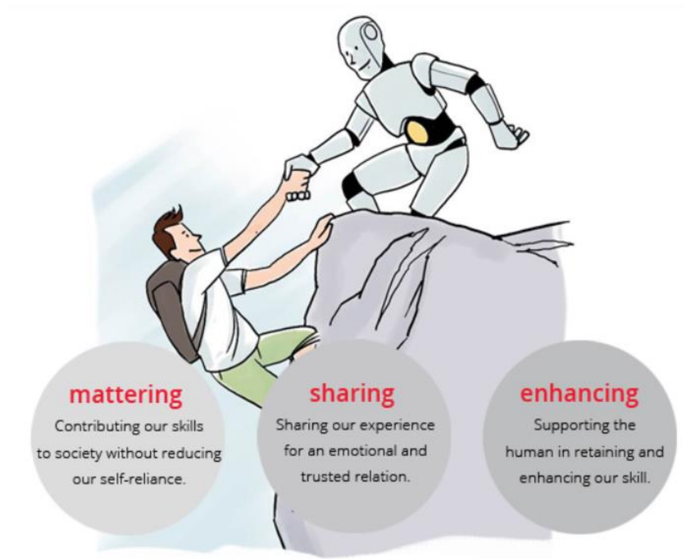
Honda Research Institutes

Cooperative Intelligence

Artificial intelligence is the ability to use optimally limited resources – including time – to achieve goals in complex environments.

Based on the defnition of intelligence by R. Kurzweil. The age of spiritual machines: When computers exceed human intelligence. Penguin, 2000.

Cooperative Intelligence is Artificial Intelligence embedded in a Social Context.



Agenda

- HRI Overview
- Examples for applications of evolutionary design optimization
  - Energy management optimization
  - Engineering design optimization
- Representations
  - Shape deformations
  - Shape morphing: Comparison of different shape deformation methods
  - Shape morphing: Evolvability for set-up of control volumes
  - Multi-objective optimization for exploration vs. exploitation
- Summary and Outlook

EC Applications –
Energy Management Optimization

Many Objective Optimization for Building Energy Systems

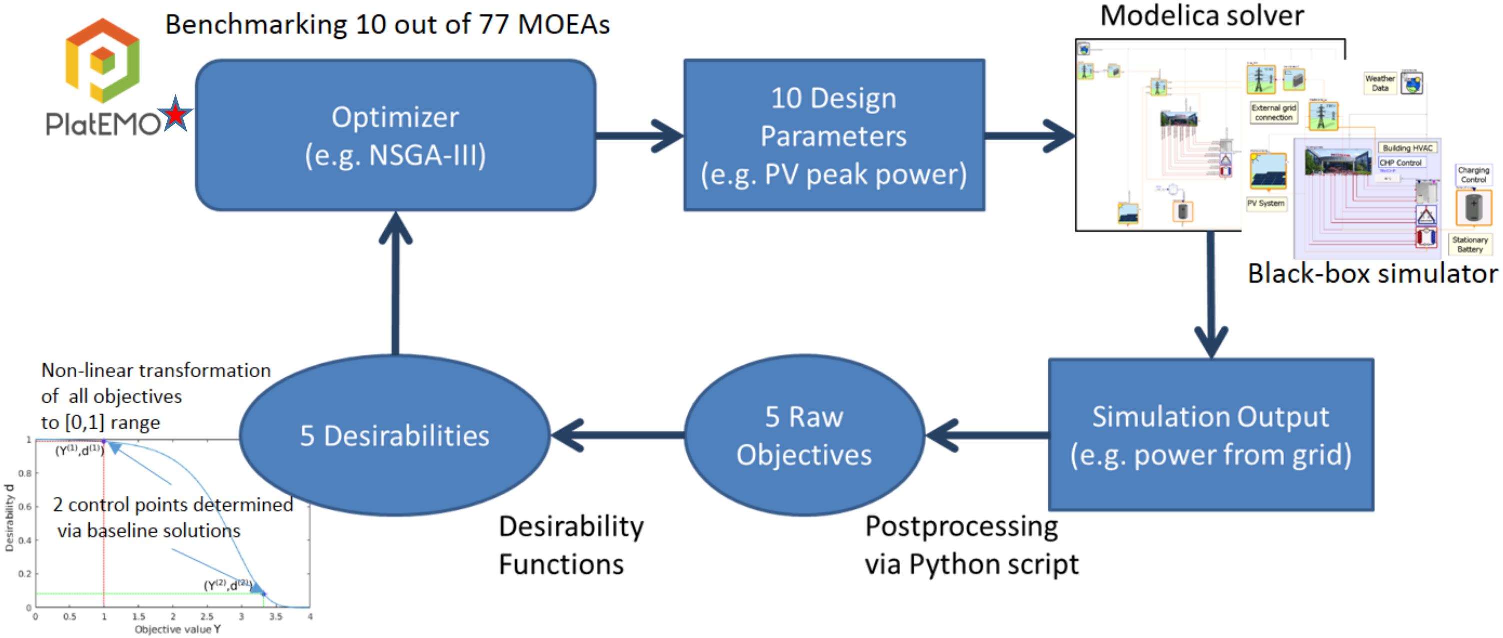
provided by Dr. Tobias Rodemann, HRI-EU

Application

Optimization of investment into new devices (battery, Photo-Voltaic, heat storage…): Minimum investment costs, annual costs, CO2 emissions and maximum resilience (emergency power supply), battery lifetime [10 design parameters, 5 objectives]

Scientific Question and Approach

- Handling of large variations in objective values (10^1-10^6) → Desirabilities
- Large number of potential MOEA algorithms (>100) → Performance comparison
- Visualization of solutions and comparison to baseline → Parallel coordinate plot, histograms

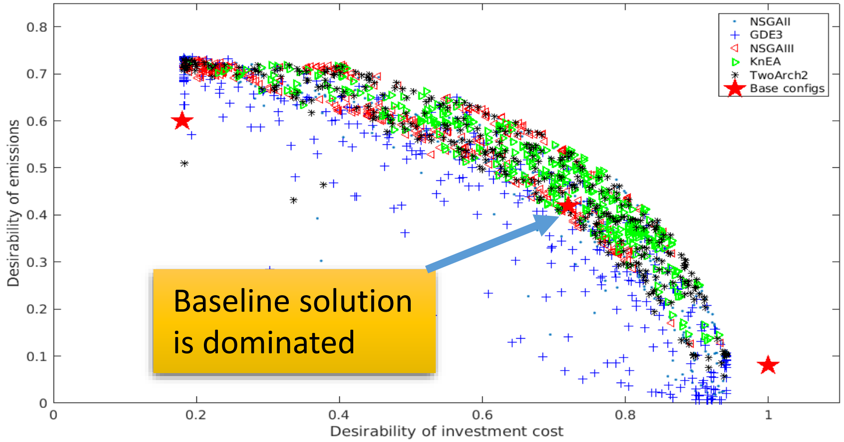


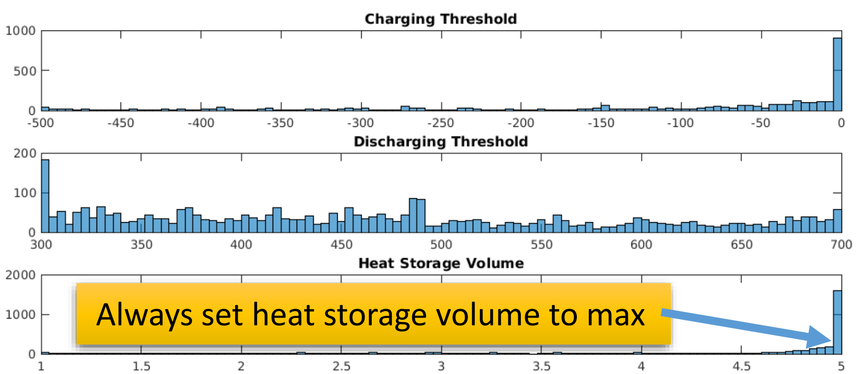
Y. Tian, R. Cheng, X. Zhang, Y. Jin, PlatEMO: A MATLAB Platform for Evolutionary Multi-Objective Optimization, IEEE Computational Intelligence Magazine, 2017

Selection of Results

provided by Dr. Tobias Rodemann, HRI-EU

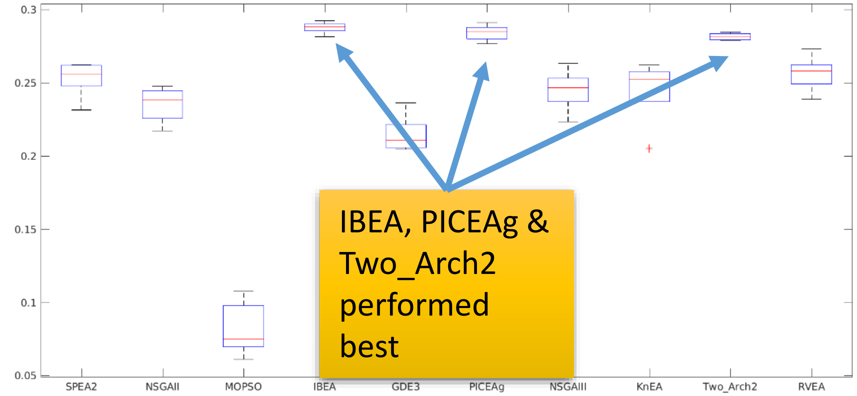
Comparing best found solutions

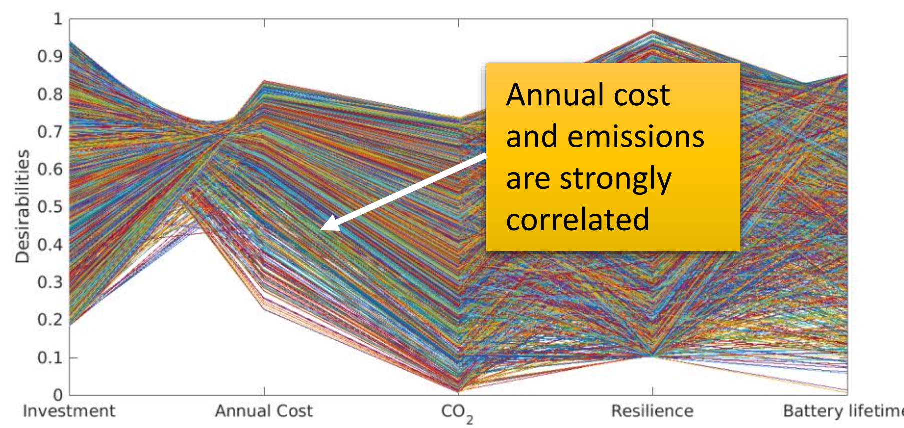




Identify reasonable values

Boxplot of 10 well-known MOEAs (10 runs each)





References:

[1] T. Rodemann & R. Unger, Smart Company Digital Twin – Supporting Controller Development and Testing Using FMI, Spring Meeting of the Japanese Society for Automotive Engineers, Yokohama, 2018

[2] T. Rodemann, A Many-Objective Configuration Optimization for Building Energy Management, IEEE WCCI, Rio, 2018

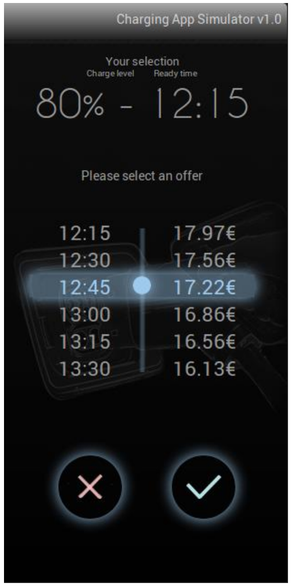
[3] T. Rodemann, A Comparison of Different Many-Objective Optimization Algorithms for Energy System Optimization, EvoAPPS (EvoStar), Leipzig, April 2019 (accepted)

Dynamic Pricing for EV Charging Considering Fairness

provided by Dr. Steffen Limmer, HRI-EU

Application

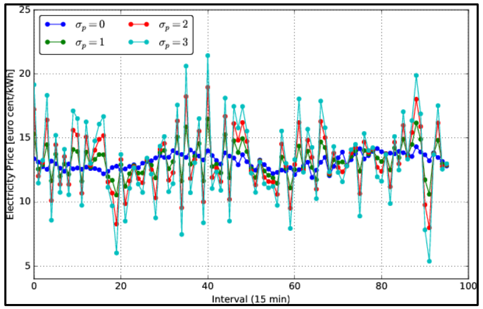
- Controlled charging to increase profit of operators of public charging stations
- Increase flexibility provided by customers through dynamic pricing
  → Deadline differentiated pricing



Scientific Question and Approach

- Issue: Dynamic prices might be perceived as unfair with negative consequences for the charging station operator
  → Investigated setting: Optimization of price offers considering the operator's profit and price fairness
- Unfairness: *unfair*^{day} - Customers with similar arrival times and similar energy requirements should get similar price offers (per kWh)

- Optimization of price offers in each interval w/ evolutionary algorithms
  - Approximation of expected profit via Monte Carlo simulation since exact preferences of customers not known
  - Single-objective optimization via self-developed EA
  - Multi-objective optimization via NSGA-II



- Experimental evaluation w/ different variances δ_P (0-3) in electricity prices

S. Limmer, M. Dietrich: *Optimization of Dynamic Prices for Electric Vehicle Charging Considering Fairness*, IEEE Symposium Series on Computational Intelligence (SSCI), pp. 2304-2311, 2018.

Experimental Results

- Results single-objective only w.r.t. expected profit:
  - ➢ High unfairness, increasing with increasing variance in operating costs

	$\delta_p = 0$	$\delta_p = 1$	$\delta_p = 2$	$\delta_p = 3$
E(daily *profit*) [Euro]	285.51	302.00	329.24	359.03
unfair^{day}	0.916	4.715	6.423	7.572

- Results single-obj. with constraint of *unfair*^{day} = 0:
  - ➢ High reduction of profit

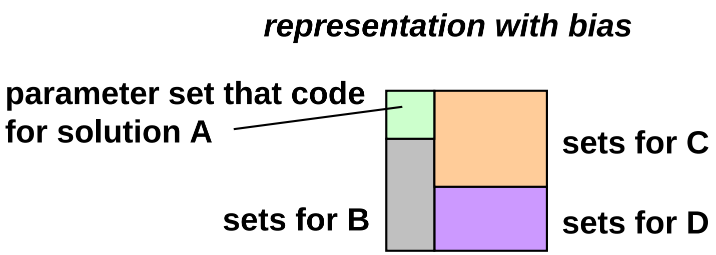
	$\delta_p = 0$	$\delta_p = 1$	$\delta_p = 2$	$\delta_p = 3$
E(*daily profit*) [Euro]	267.77	269.27	284.77	298.31
unfair^{day}	0.0	0.0	0.0	0.0
Δ(profit)	-6.21%	-10.84%	-13.51%	-16.91%

- Results multi-obj. with choosing solutions with highest profit from Pareto fronts
  - ➢ Significantly reduces unfairness without impact on profit

	$\delta_p = 0$	$\delta_p = 1$	$\delta_p = 2$	$\delta_p = 3$
E(*daily profit*) [Euro]	285.58	302.13	329.27	359.12
unfair^{day}	0.257	0.374	0.527	0.532

EC Applications – Engineering Design Optimization

Common Principles



- ***regularity***

  no solutions should be favoured solely by the representation

- ***strong causality***

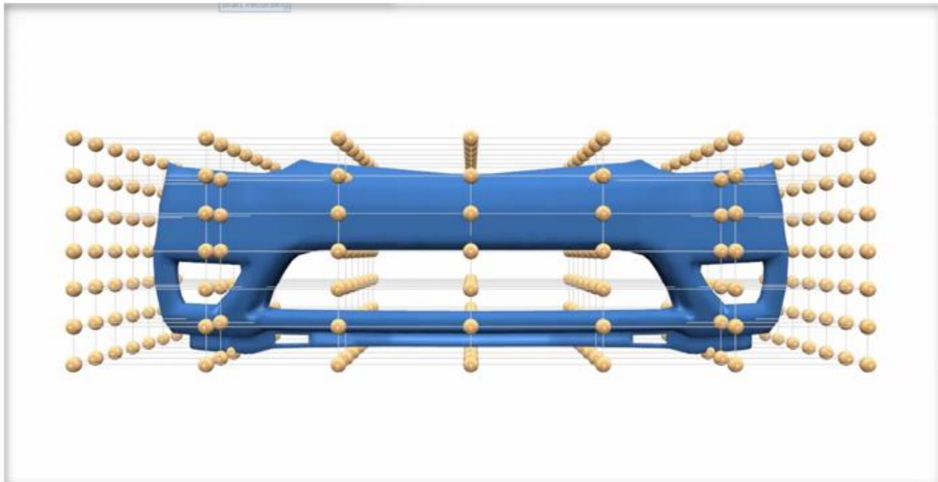
  the variation induced neighbourhood relation in both spaces should be conserved under the genotype – phenotype mapping

- ***completeness***

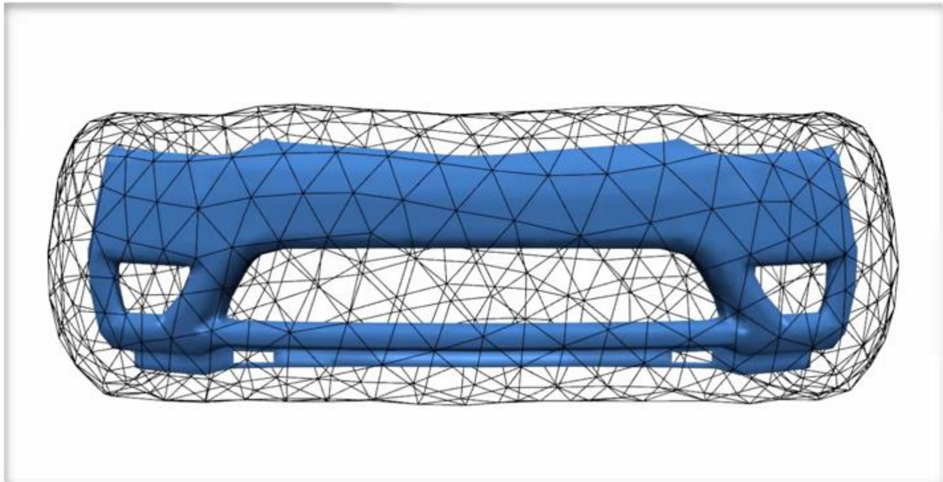
  all feasible solutions should be reachable with the representation

High-quality shape representations strongly influence the success of optimizations

Representations: Shape Morphing

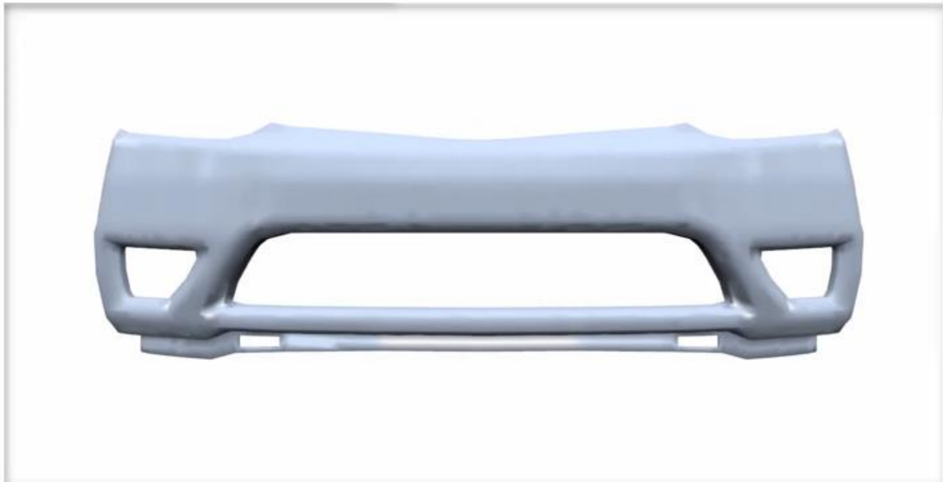


Free-form deformation (FFD)



Cage deformation

Space deformation (RBF)



Shell based deformation

Evolutionary Optimization of Turbine Blades

provided by Dr. Sebastian Schmitt, HRI-EU

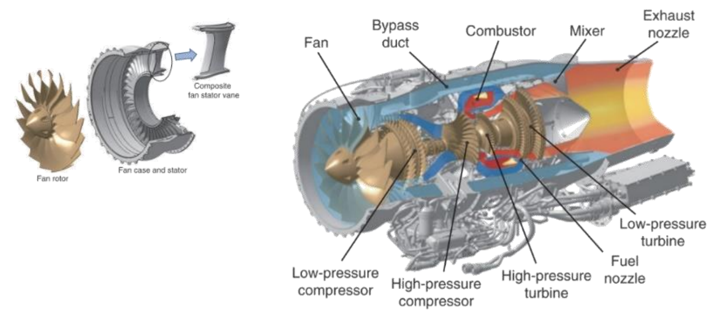
Background

- GE Honda develops turbofan engine HF120 for HondaJet
- Many components need to be optimized during design process
  - ⇒ Improve aerodynamic efficiency of fan blade
- Accurate CFD simulations with realistic conditions are very resource consuming

Problems

- Only few optimization runs can be done
  - ⇒ How representative/reproducible are obtained results
    local minima? Initialization? Evaluation noise? Setup variations?
- What representation for geometry changes?
  - Number of parameters
  - ⇒ Expected tradeoff between achievable efficiency and number of parameters:

    More parameters ⇔ higher flexibility ⇔potentially better improvement ⇔ but more evaluations necessary: true?!?
- Which optimization algorithm?



GE Honda HF120 turbofan engine

Target

- Get better understanding of fitness landscape for real-world turbo-fan optimization problem
- How much variation exists when running same or similar optimizations multiple times:
  - in performance (efficiency)? in actual design/geometry?

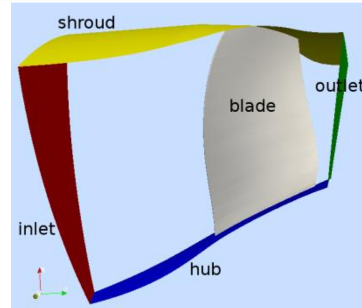
J. Kmec, S. Schmitt, Exploring the Fitness Landscape of a Realistic Turbofan Rotor Blade Optimization. EngOpt 2018 Proc. of the 6th International Conference on Engineering Optimization. Springer, 2019

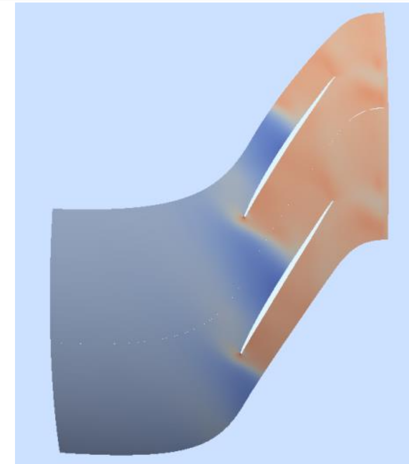
Evolutionary Optimization of Turbine Blades

provided by Dr. Sebastian Schmitt, HRI-EU

CFD Simulation setup

- Flow in fan rotor passage
  - Trans-sonic compressible flow
  - OpenFOAM setup (~ 96 cpu-hours for one evaluation)
  - Cruise operating condition (rpm, mass flow rate)



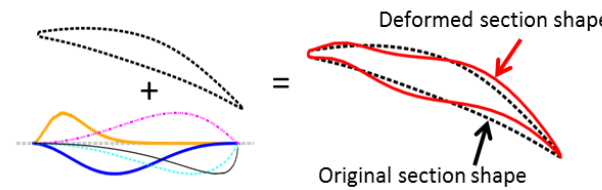


Optimization setup

- Fitness function (minimized)

$$f = 1 - \frac{\eta_{\text{cruise}}}{\eta_{\text{base,cruise}}} + \text{Penalties}$$

Penalty term ensures converged flow

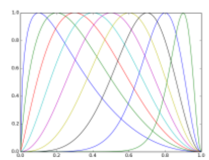


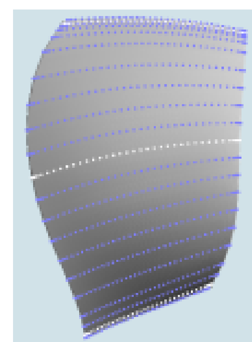
Blade deformation representation

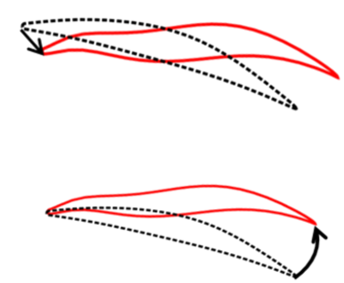
- Three deformable sections: hub, mid-span, shroud
  (other sections are interpolated)
- Deform sections with Hicks-Henne shape functions
- Also move and rotate sections
- Number of shape functions per section $N_{\text{HH/section}} \in [3{,}12]$

$\Rightarrow$ Dimensionality of representation:

$$D = 3\,(N_{\text{HH/section}} + 3) \in [18, 45]$$





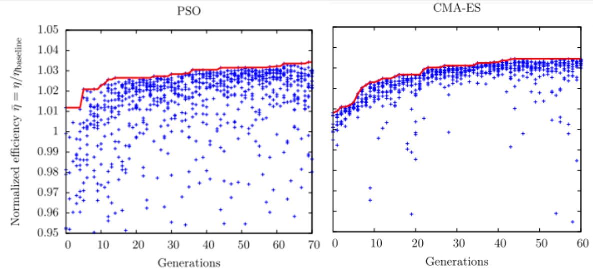


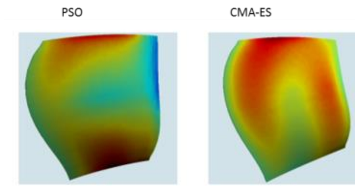
Evolutionary Optimization of Turbine Blades

provided by Dr. Sebastian Schmitt, HRI-EU

Influence of optimization algorithm

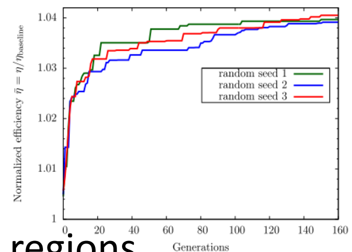
- More explorative search in PSO: step-size and initialization
- Similar efficiency improvements
  - PSO: $\Delta\eta_{\mathrm{rel}} = 3.42\%$
  - CMA-ES: $\Delta\eta_{\mathrm{rel}} = 3.45\%$
- Geometries: qualitative differences in aerodynamically sensitive regions

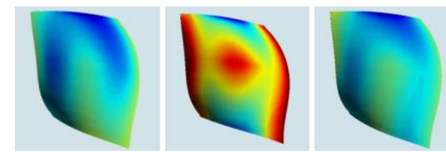




Influence of random initialization

- Similar efficiencies
  - Seed 1: $\Delta\eta_{\mathrm{rel}} = 3.97\%$, Seed 2: $\Delta\eta_{\mathrm{rel}} = 3.91\%$, Seed 3: $\Delta\eta_{\mathrm{rel}} = 4.05\%$
- Geometries: qualitative differences in aerodynamically sensitive regions

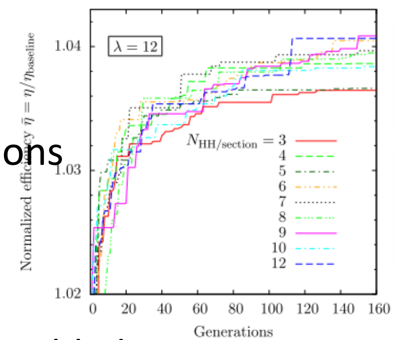


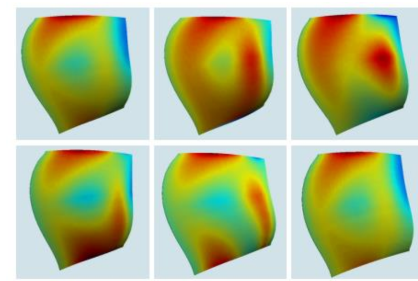


Green: similar geometry as baseline
Red: geometry deformed into picture (away from viewer)
Blue: geometry is deformed toward viewer

Influence of dimensionality of representation

- No clear trend in optimization progress
- No clear trend for achievable efficiency improvement
- Geometries: qualitative differences in aerodynamically sensitive regions



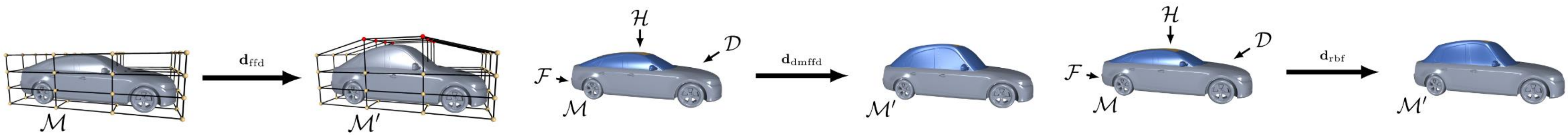


Conclusions

- All the tested variants achieve comparable improvements
- Optimized geometries showed substantial variation over the complete blade geometry
- Even minor changes lead to very different geometries
- Fitness landscape is highly multi-modal with many local minima and small basins of attractions

Representations – Shape Morphing

Shape Morphing - Challenges



<u>Shape Morphing</u>

- Operation to transform an initial design to a deformed design
- Mapping of discretized surface by spline functions or RBF kernels
  (i.e. many surface points are reduced to a lower number of parameters)
- For EC: Optimal trade-off needs to be found for minimum parameters with maximal shape flexibility
- For EC: Shape morphing allows online adaptation of parameter number for more local deformations
- [For CFD/FE simulations: simultaneous deformation of design and numerical grid]

<u>2-level Challenge</u>

- Higher level: Comparison of different deformation types
- Lower level: Optimal number and distribution of initial control points or RBF kernels

⇨ *„The Value of Evolvability“*

Evolvability – Complex Systems Engineering

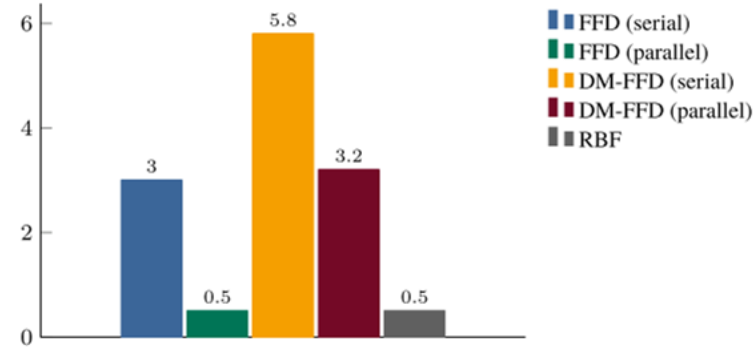
<u>*Potential Definitions*</u>

- Evolvability is an evolved quality and is specified as the ability of the configuration space (in this case, the space of genotypes and phenotypes) to produce an endless supply of viable configurations with remarkably few obvious dead-ends
  A. A. Minai, D. Braha, and Y. Bar-Yam, "Complex Engineered Systems: A New Paradigm," in Complex Engineered Systems, D. Braha, A. Minai, Y. Bar-Yam (Eds.), Springer, Berlin, 2006
- Evolvability is considered in the sense of the capacity of a system to produce favorable phenotypic variations of a design within a moderate number of generations while avoiding non-feasible mutations
  H. Lehmann, and S. Menzel, "Evolvability as the Concept for the Optimal Design of Free-Form Deformation Control Volumes," in IEEE Congress on Evolutionary Computation (CEC), Brisbane, 2012

- Produce favorable solutions → Performance increase
- Moderate number of generations → Time
- Avoid non-feasible mutations → Search space and direction

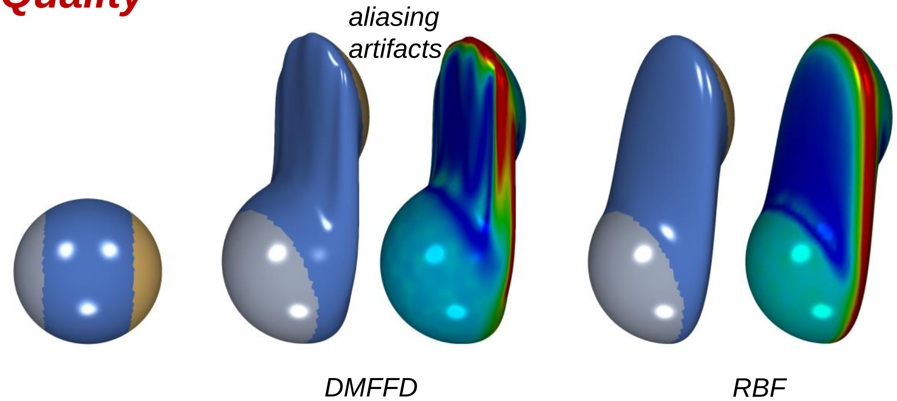
Comparison of Deformation Types

Computational Performance



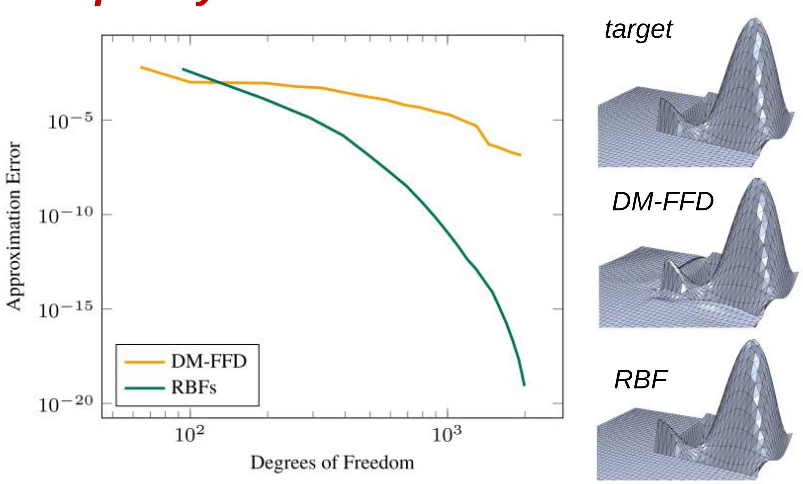
performance comparison

Quality

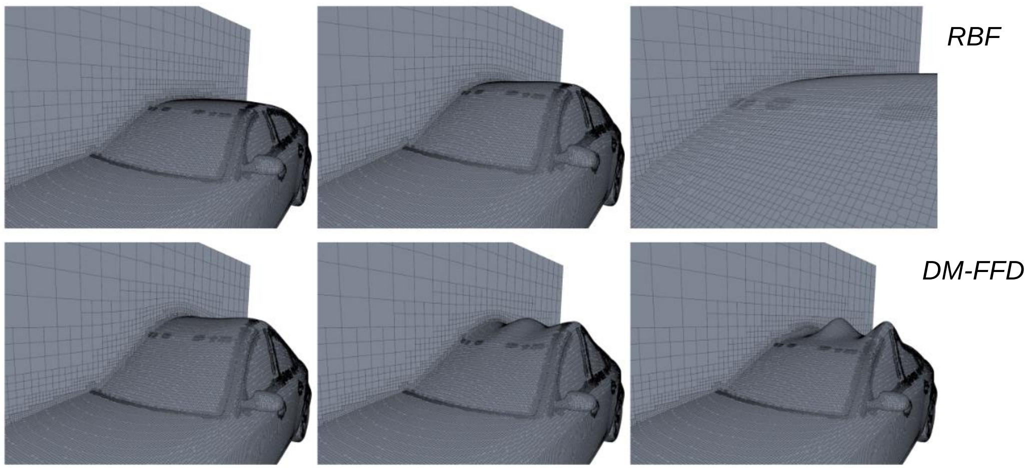


mesh smoothness based on mean curvature visualizations

Adaptivity

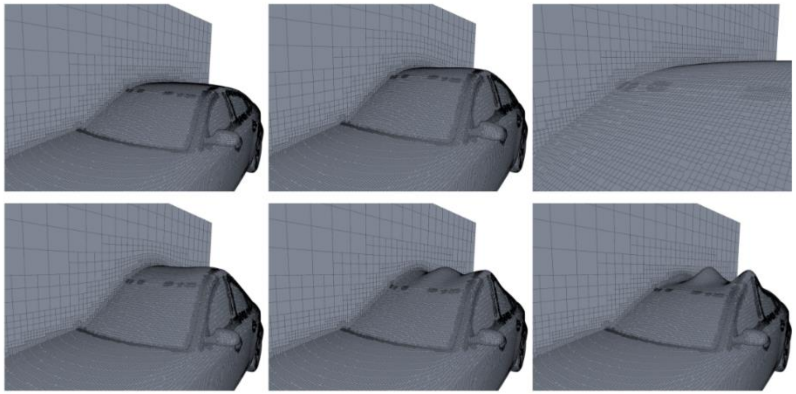


Mesh Quality



D. Sieger, S. Menzel, and M. Botsch, “On Shape Deformation Techniques for Simulation-based Design Optimization,” in New challenges in grid generation and adaptivity for scientific computing, SEMA SIMAI Springer Series, 2015

Comparison of Deformation Types



	Aspect Ratio	Cell Orthogonality	Face Skewness	Face Pyramids
Original	6.9 ✓	64.7 ✓	3.4 ✓	✓
RBF	6.6 ✓	68.6 ✓	3.7 ✓	✓
DM-FFD-10	7.0 ✓	71.3 !	3.6 ✓	✓
DM-FFD-15	7.0 ✓	70.7 !	3.4 ✓	✓
DM-FFD-25	2.5e+195 ✗	179.7 ✗	1031.8 ✗	✗

Mesh Quality (cont.) *OpenFOAM CFD solver mesh check*

	Performance	Robustness	Quality	Adaptivity	Precision
FFD	○	+	○	−	−
DM-FFD	−	○	○	−	○
RBF	○	+	+	+	+

Summary

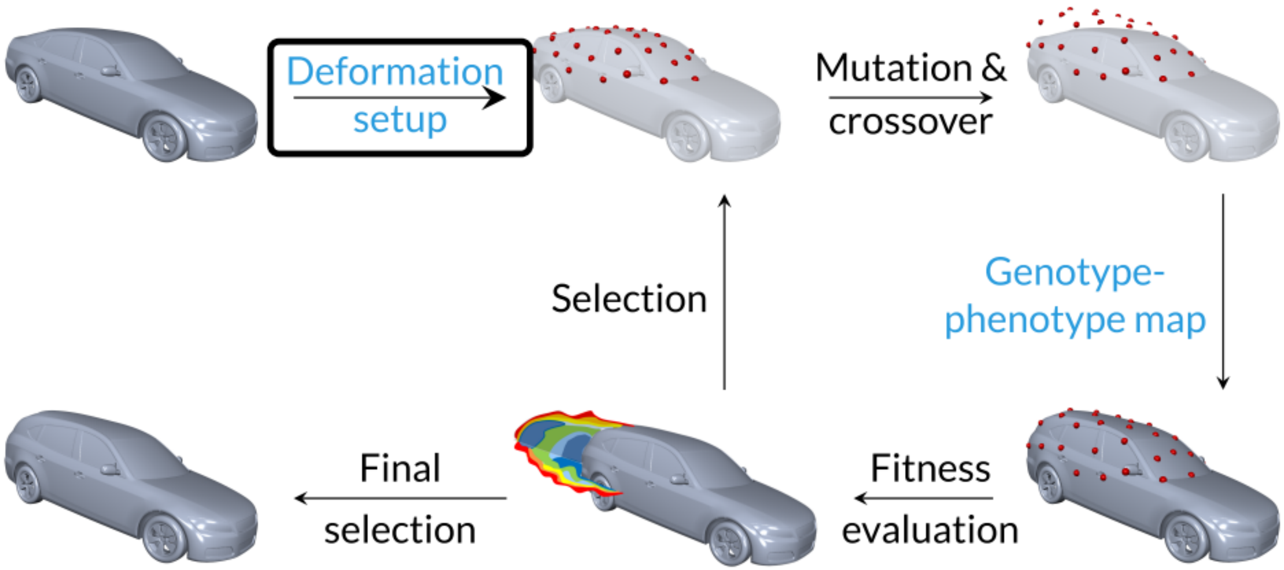
"Evolvability perspective"

- RBF deformations comprise the highest potential to successfully generate valid designs within the mutation step of an evolutionary design optimization
- FFD is a recommended method if fast and simple conceptual design exploration should be robustly achieved

Optimal Deformation Set-Up

Engineering Design Optization

- Initial deformation set-up: minimum parameter number w/ max. flexibility
- Initial deformation set-up: strong influence on search efficiency



Challenges

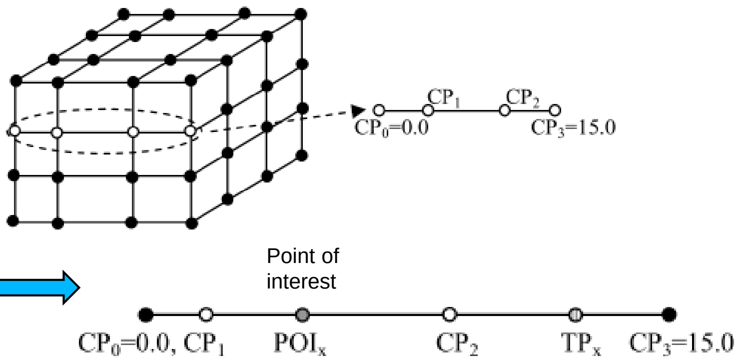
- Human set-up: time consuming process, typically shape feature based (less surprising)
- Development of computational set-up method which integrates historic data

A. Richter, J. Achenbach, S. Menzel, and M. Botsch, "Evolvability as a quality criterion for linear deformation representations in evolutionary optimization," in Proceedings of IEEE Congress on Evolutionary Computation, pp. 901–910, 2016.
A. Richter, S. Dresselhaus, S. Menzel, and M. Botsch, "Orthogonalization of linear representations for efficient evolutionary design optimization," in GECCO, Japan, 2018.

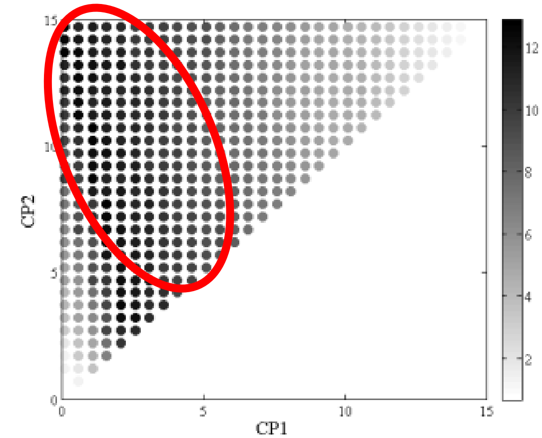
Optimal Deformation Set-Up

Initial idea and early experiments

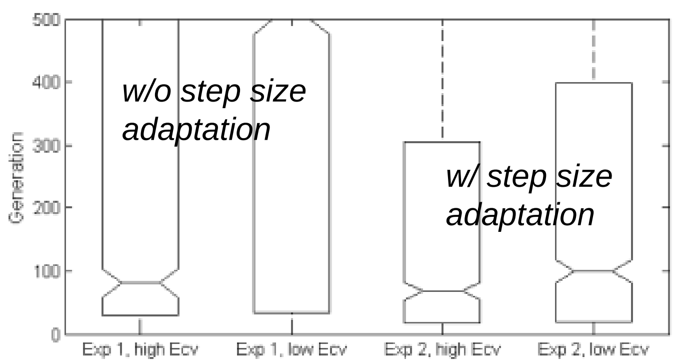
- Simplified FFD control volume



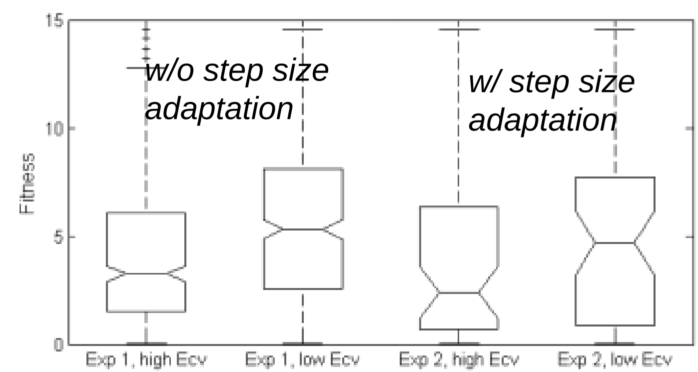
Modify CP1 and CP2 and count the number of unmodifed POI



Experimental results (Evolutionary target matching optimization)



Evolutionary target matching experiment



Distance of non-matched optimizations

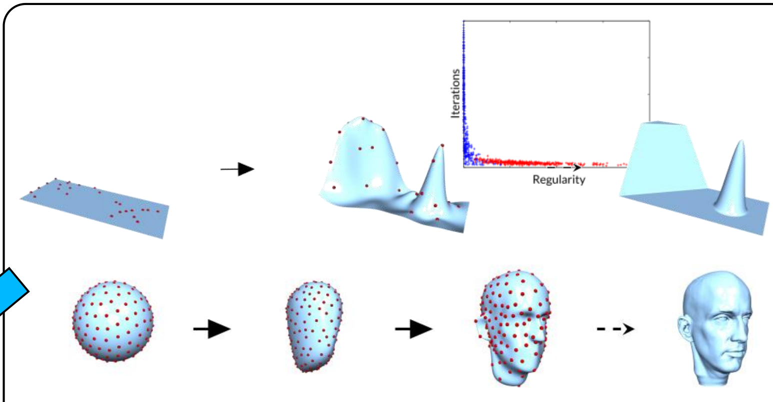
Control volumes w/ higher evolvability converge faster; better fitness after fixed number of iterations

S. Menzel, “Evolvable free-form deformation control volumes for evolutionary design optimization,” in IEEE Congress on Evolutionary Computation, IEEE, New Orleans, pp. 1388-1395, 2011

Optimal Deformation Set-Up

Generalization

- Linear Deformation Representations: M´ = M + Up
- Deformation Matrix: U



A. Richter, J. Achenbach, S. Menzel, and M. Botsch, "Evolvability as a quality criterion for linear deformation representations in evolutionary optimization," in Proceedings of IEEE Congress on Evolutionary Computation, pp. 901–910, 2016

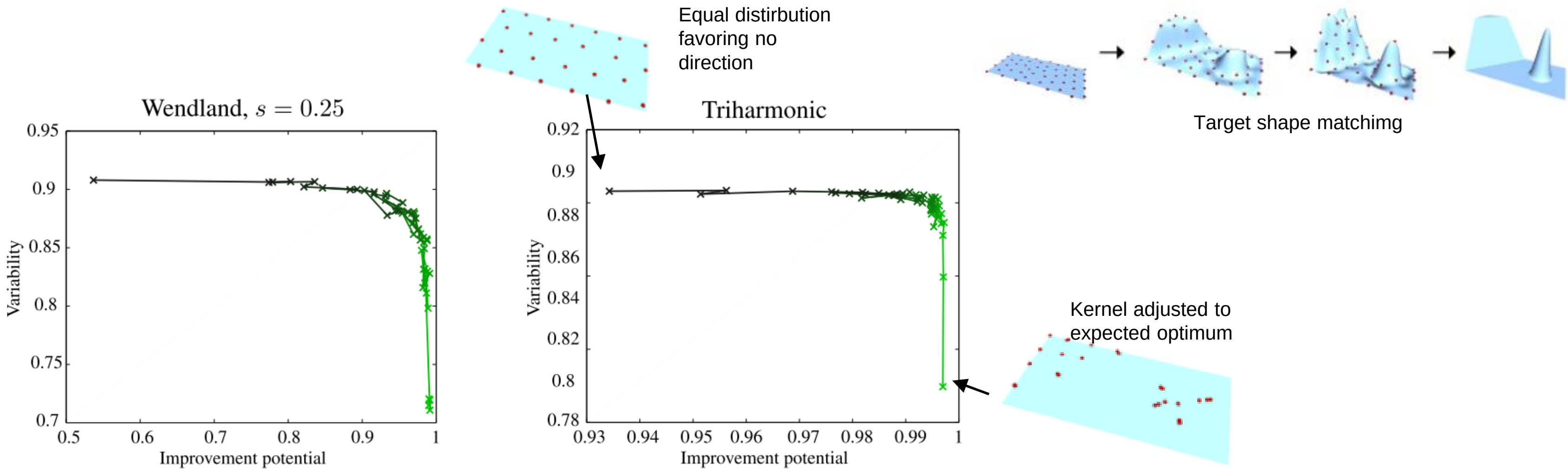
Evolvability

Variability	Regularity (Locality)	Improvement Potential
Exploration	Convergence speed	Exploitation
Infill distance		Gradient information
$V = (X_d - h_{X,C})/X_d,\ V \in [0,1]$ $h_{X,C} = \sup \min \lVert x-c \rVert,\ x \in X,\ c \in C$	Orthogonalization of deformation matrix (e.g. SVD)	$P(U) = 1 - \lVert (I - UU^{+})g \rVert^2,\ P \in [0,1]$
Targets equally spaced kernel/control point distribution	Improves convergence speed of evolutionary opt.	Targets kernel/control point distribution to match given data

A. Richter, "Evolvability-guided Optimization of Linear Deformation Setups for Evolutionary Design Optimization," Doctoral Dissertation, Bielefeld University, 2019 (to appear).

A Computational Method for Deformation Set-up

- Multi-objective optimization for “Variability” (Infill distance) and “Improvement potential” (gradient information): Exploration vs. exploitation
- Gradient information options:
  - Initial information based on shape information (human heuristics)
  - Initial information based on existing historic data
  - Online adaptation of set-up while gathering information during optimization



- Optimal convergence speed: “Regularity” by orthogonalization

A. Richter, “Evolvability-guided Optimization of Linear Deformation Setups for Evolutionary Design Optimization,“ Doctoral Dissertation, Bielefeld University, 2019 (to appear).

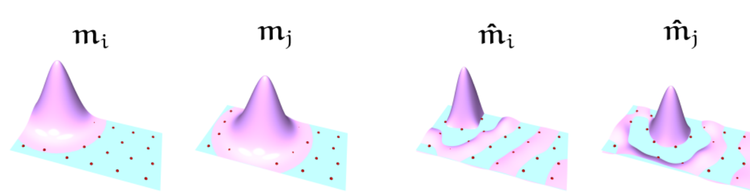
"Regularity" by Orthogonalization

Regularity

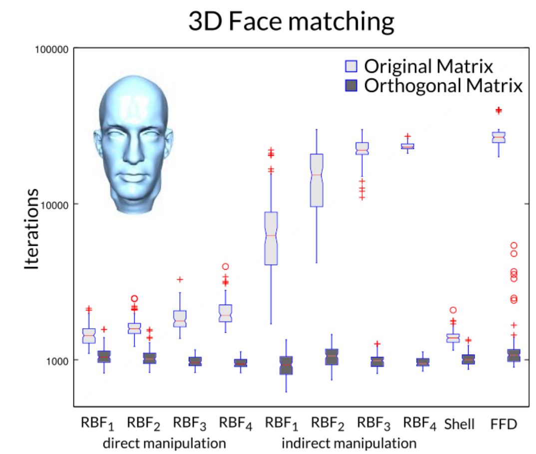
- Defined as condition number of deformation matrix
- Force R = 1 by orthogonalization

$$R(\mathbf{M}) = 1$$
$$\uparrow$$
$$\kappa^{-1}(\mathbf{M}) = \frac{\sigma_{min}}{\sigma_{max}} = 1$$
$$\uparrow$$
$$\sigma_{min} = \sigma_1 = \cdots = \sigma_n = \sigma_{max} = 1$$

$$M = U\Sigma V^T \xrightarrow[\text{transformation}]{\text{Basis}} \hat{M} = UV^T$$



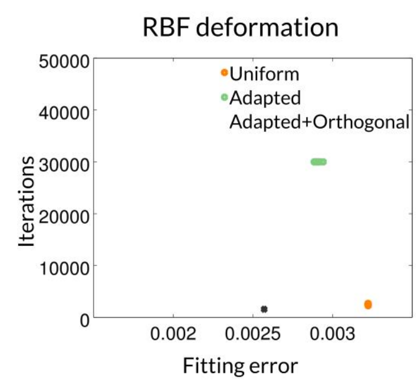
$m_i^T m_j \neq 0$ $\qquad$ $\hat{m}_i^T \hat{m}_j = 0$

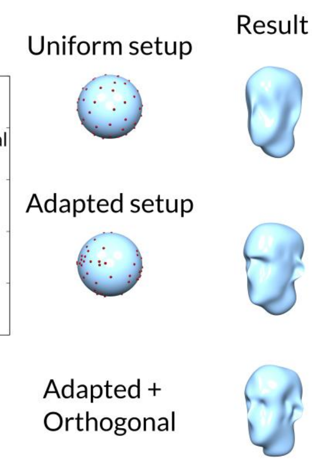


Example: Evolutionary Face Matching Optimization

- Uniform set-up: fast but worse fitness
- Adapted set-up: slow but better fitness
- Adapted + orthogonal: fast and good fitness!

- Orthogonalization speeds up convergence
- Disadvantage: Unintuitive for a human-based opt.





Summary and Outlook

Summary

- Evolvability criteria provide potential characteristics for developing computational methods to find optimal representations
- Optimal representations allow efficient evolutionary search
- Shape morphing methods:
    - High level comparisons favor RBF deformations for practical applications;
      FFD is promising for initial robust trials to learn about the shape and performance
    - Deformation set-ups can be computed using a multi-objective optimization for an optimal trade-off between exploration and exploitation
    - Orthogonalization of deformation matrix increases convergence speed

Outlook

- Evaluation of shape morphing set-up in aerodynamic optimization
- Evaluation of shape morphing set-up for Hicks-Henne splines
- Evaluation of shape morphing set-up in dynamic optimization problems using online learning

Thank you for your attention