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A general surface reconstruction method for post-processing of topology optimisation results

Giulia Bertolino, Giulio Costa, Marco Montemurro, Nicolas Perry and Franck Pourroy SIM-AM 2019, PAVIA, ITALY, 11-13 SEPTEMBER 2019













Outline



Context and scientific objectives



Surface Reconstruction strategy for genus 0 open surfaces



Poly-patches strategy for genus N surfaces (open and closed)



Conclusions and perspectives

13/09/2019

Context and scientific objectives

Surface Reconstruction strategy for genus 0 open surfaces

Poly-patches strategy for genus N surfaces (open and closed)

Conclusions and perspectives

Appendix

Context and scientific objectives

Context

Topology optimisation:

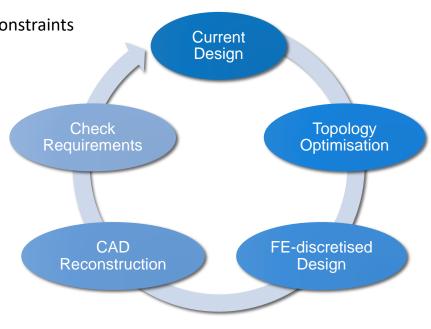
Optimal distribution of material in a prescribed domain

Minimise an objective/cost function + meet optimisation constraints

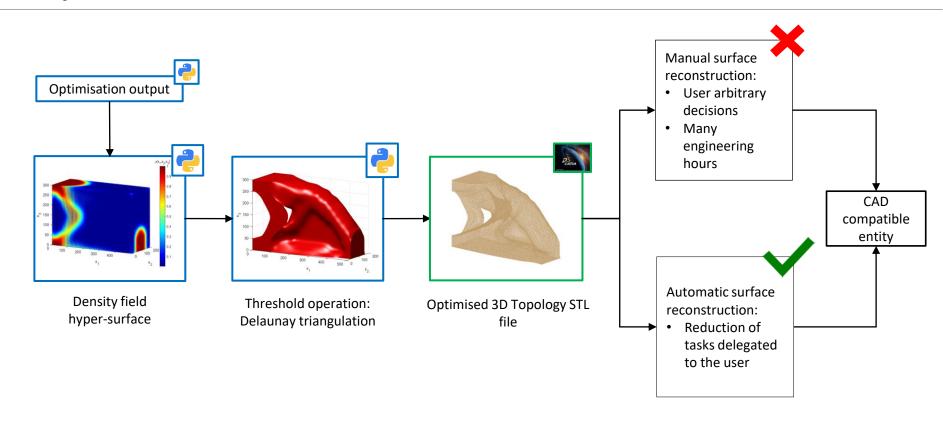
Results of topology optimisation strategy:

- Density field described by element-wise format
- Need to obtain smooth surfaces
- How is it possible to obtain CAD compatible entity?





Objectives



Context and scientific objectives

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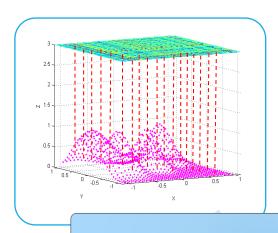
Appendix

Surface Reconstruction strategy for genus 0 open surfaces

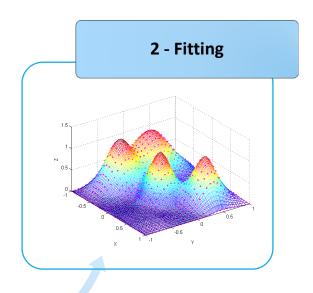
Proposed strategy: main ingredients

Mapping the STL points

Find the planar triangulation P isomorphic to the given triangulated graph G



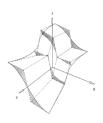
1 - Parameterisation



Least squares minimisation

Obtain the optimal set of NURBS parameters (Degrees, Knot vector, Weights)

Parameterisation



Projection method [Piegl,1995] - open, genus 0, not folded

Mercator's projection method [Rahi,2007] - closed, genus 0



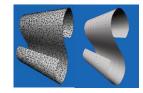






Global conformal method [Gu,2003] - closed, genus N

Shape preserving method [Floater,1997] - open, genus 0, folded



Shape preserving method: capabilities and main features

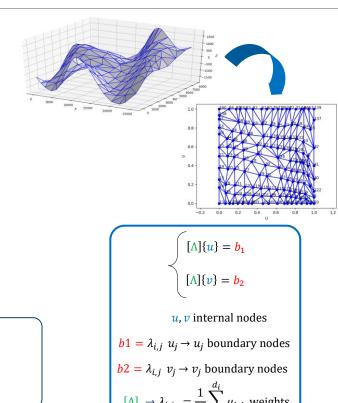
Find (u, v) parameters associated to the Cartesian coordinates of the 3D Euclidean space

Relabel nodes of STL file: **internal nodes** and **boundary nodes** (ordered in anti-clockwise sequence)

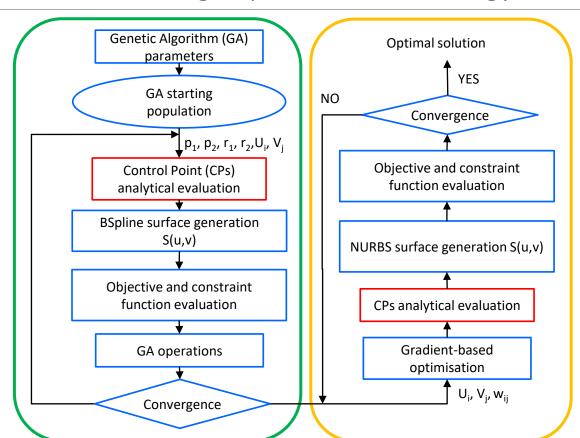
Parameterisation of the boundary nodes by chord length method into the boundary of a convex polygon $D \in \mathbb{R}^2$ $[0,1] \times [0,1]$

Expression of each internal node as linear convex combination of neighbours.

- Evaluation of the weights λ_{i,j_k} for each neighbour
- Preserving distances and angles between 3D and 2D



Surface fitting: Optimisation strategy



Part A

Originality: NURBS surface parameters (degree, CPs number, Knot Vector (KV) components) will be find automatically by the GA (in the literature there are no rules to set these parameters)

Part B

Local refinement of the minimum found by the GA ⇒ improvement of the solution in terms of KV COMPONENTS and WEIGHTS

Problem formulation and numerical aspects: genetic optimisation

Part A

Objective function

$$\min f(\mathbf{x}) = \left(\sum_{k=0}^{n_{tp}} ||S(u_k, v_k) - Q_k||^2 + \lambda J\right)^{\frac{1}{r_1 + r_2}} \text{ such that}$$

- Distance between BSpline entity and target points
- Thin-plate spline energy functional Floater, 2000]: smoothing term

$$J = \int_{a_1}^{b_1} \int_{a_2}^{b_2} S_{uu}^2 + 2S_{uv}^2 + S_{vv}^2 \, du \, dv$$

Constraint function:

Non singularity of Basis Functions (BF) matrix

$$g_1(\mathbf{x}) = \dim(BF) - \rho(BF) \rightarrow BF = [N_u N_v]^T [N_u N_v] + \lambda E$$

- Dimension of the basic functions matrix
- Rank of the matrix of the basic functions matrix
- Smoothing matrix

Design variables

Discrete variables:

- p₁, p₂ → Degrees of the Bspline entity
- r₁, r₂ → Number of non-trivial components of KV

Continuous variables:

• $U_{p1+2, ..., }U_{p1+r1+2}, V_{p2+2, ..., }V_{p2+r2+2} \rightarrow$ Knot vector components

Design space dimension = $4 + r_1 + r_2$

Discrete variables values affect the dimension of the Continuous variables module.

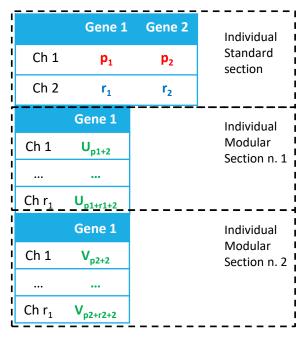
Problem formulation and numerical aspects: genetic optimisation

Part A

GA ERASMUS[Montemurro,2018] capabilities:

- <u>Reproduction among individuals</u>: crossover and mutation operations
- <u>Reproduction among species</u>: on individuals with different number of chromosomes
- <u>Penalisation:</u> Automatic Dynamic Penalisation (ADP)
 - Automatically and adaptively updating the coefficients of penalisation
 - Preventing infeasible solutions
 - Efficient exploration of the boundary of the feasible domain

Genotype



Ch = chromosome

Problem formulation and numerical aspects: deterministic optimisation

Part B

Design variables (only continuous)

$$\mathbf{X} \begin{cases} \mathbf{U} = \{0, ..., 0, u_{p+1}, ... u_n, 1, ..., 1\} \\ \mathbf{V} = \{0, ..., 0, v_{q+1}, ... v_m, 1, ..., 1\} \\ \mathbf{W} = \begin{pmatrix} w_{11} & \cdots & w_{1n_2} \\ \vdots & \ddots & \vdots \\ w_{n_11} & \cdots & w_{n_1n_2} \end{pmatrix} \end{cases}$$

Objective function

$$\min f(\mathbf{x}) = \sum_{k=0}^{n_{tp}} ||S(u_k, v_k) - Q_k||^2 + \lambda J \text{ such that:}$$

Constraint function

$$g_1(\mathbf{x}) = \dim(BF) - \rho(BF) \rightarrow BF = [N_u N_v]^T [N_u N_v] + \lambda E$$

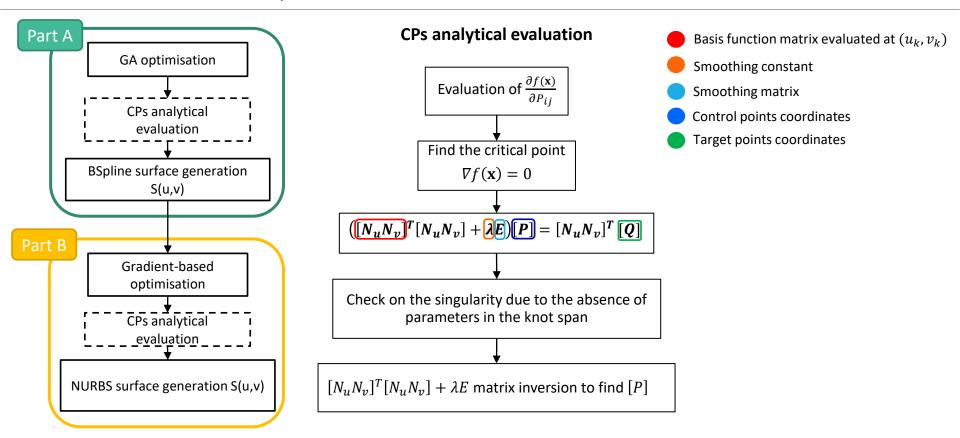
Non trivial KV components

ullet Numerical evaluation of $abla f(\mathbf{x})$ respect to KV

Weights

• Analytical evaluation of $\nabla f(\mathbf{x})$ respect to weights

Focus on the analytical CPs evaluation



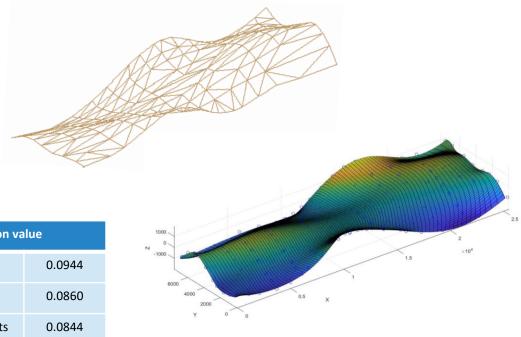
Numerical results: 1st benchmark

	Design variables	Lower - Upper bounds
GA optim	Degree (p)	2 – 6
	N° of KV's components (r)	1 – 17
	KV's components values (U, V)	0.001 - 0.999
Grad optim	Alpha, Beta (KV's components values)	0.001 – 0.999
	Weights (w)	0 – 10

Design space

Optimised values		Objective function value	
Degree (p ₁ -p ₂)	5 – 5	GA phase	0.0944
N° of KV's components (r ₁ -r ₂)	1-1	Grad KV	0.0860
KV's components values (U, V)	0.374 - 0.599	Grad KV + Weights	0.0844

Optimised design variables at the end of the Surface Reconstruction algorithm and objective function value evolution along the different phases



Results of the Surface Reconstruction strategy

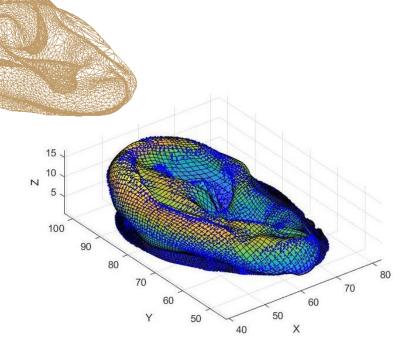
Numerical results: 2nd benchmark

	Design variables	Lower - Upper bounds
GA optim	Degree (p)	2 – 6
	N° of KV's components (r)	16 – 35
	KV's components values (U, V)	0.001 – 0.999
Grad optim	Alpha, Beta (KV's components values)	0.001 – 0.999
	Weights (w)	0 – 10

Design space

Optimised values		Objective function value	
Degree (p ₁ -p ₂)	2 – 2	GA phase	0.963576
N° of KV's components (r ₁ -r ₂)	19 – 19	Grad KV	0.954653
		Grad KV + Weights	0.892313

Optimised design variables at the end of the fitting algorithm and objective function value evolution along the different phases



Results of the Surface Reconstruction strategy

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Surface Reconstruction strategy for genus 0 open surfaces

Poly-patches strategy for genus N surfaces (open and closed)

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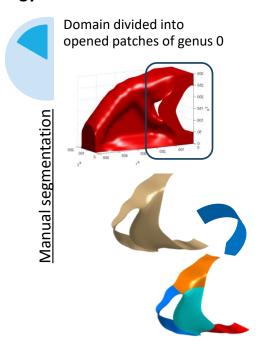
Poly-patches strategy for genus N surfaces (open and closed)

Poly-patches strategy for genus N surfaces (open and closed)

Aim: Application of the Surface Reconstruction strategy to **surfaces** (open and closed) with **holes** (genus > 0)

Parameterisation

Strategy:



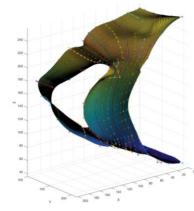
Adjacent patches have same parameters along boundary

Proper roto-translation of patches according to the global reference system



Automatic calculation of NURBS parameters Automatic imposition of CO and C1 continuity condition between patches





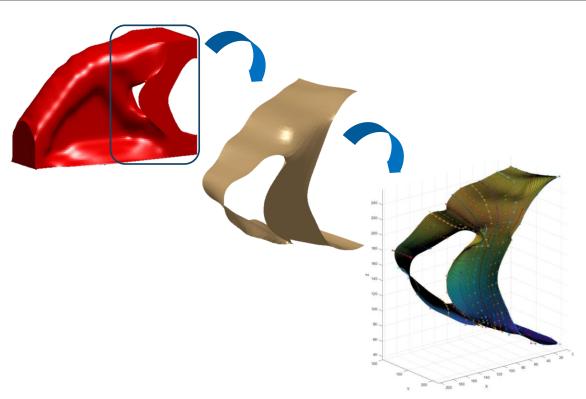
Numerical result

	Design variables	Lower - Upper bounds
GA optim	Degree (p)	2-6
	N° of KV's components (r)	4 – 20
	KV's components values (U, V)	0.001 – 0.999
Grad optim	Alpha, Beta (KV's components values)	0.001 – 0.999
	Weights (w)	0 – 10

Design space

Optimised values	
Degree (p ₁ -p ₂)	2 – 2
N° of KV's components (r ₁ - r ₂)	8 – 8

Optimised design variables at the end of the fitting algorithm.



Results of the Surface Reconstruction strategy

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Conclusions and perspectives

Conclusions

- Automatic optimisation of approximation surface parameters
- > Reduction of tasks delegated to the user

Perspectives

- Mapping methods for genus > 0 surfaces
- Automatic segmentation of the triangulation (STL file)
- Integration of Tspline entities in the surface fitting





Thank you for your attention

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Context and scientific objectives

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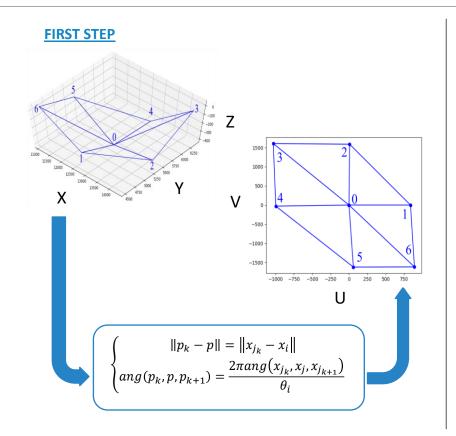
Conclusions and perspectives

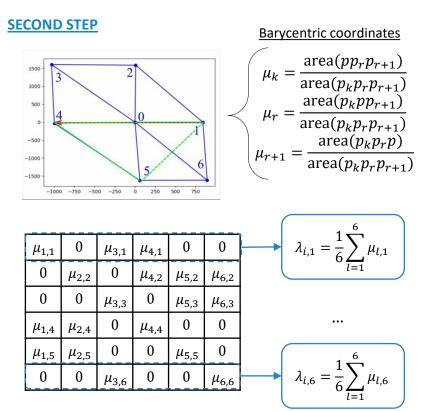
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Shape preserving method^[Floater,1997]





Thin-plate spline energy^[Floater,2000]

Adding a smoothing term in the surface approximation of unstructured data aims to find a unique solution.

$$f(\mathbf{x}) = \sum_{k=0}^{n_{tp}} \|S(u_k, v_k) - Q_k\|^2 + \lambda J \qquad \int J = \int_{a_1}^{b_1} \int_{a_2}^{b_2} S_{uu}^2 + 2S_{uv}^2 + S_{vv}^2 \ du \ dv \rightarrow \text{simple thin plate energy functional} \\ \lambda \rightarrow \text{constant measuring the trade off between approximation and smoothing}$$

Find the minimum \rightarrow normal equations

$$\frac{\partial f(\mathbf{x})}{\partial P_{ii}} = ([N_u N_v]^T [N_u N_v] + \lambda E)[P] - [N_u N_v]^T [Q] = 0$$

Where E is a (n_1n_2) x (n_1n_2) matrix whose elements are:

$$E_{ijrs} = A_{ijrs} + 2B_{ijrs} + C_{ijrs}$$

$$\begin{cases}
A_{ijrs} = \int_{a_1}^{b_1} N_i''(u) N_j''(u) du \int_{a_2}^{b_2} N_j(v) N_s(v) dv \\
B_{ijrs} = \int_{a_1}^{b_1} N_i'(u) N_j'(u) du \int_{a_2}^{b_2} N_j'(v) N_s'(v) dv \\
C_{ijrs} = \int_{a_1}^{b_1} N_i(u) N_j(u) du \int_{a_2}^{b_2} N_j''(v) N_s''(v) dv
\end{cases}$$

And λ is:

$$\lambda = \frac{\|([N_u N_v]^T [N_u N_v])^2\|}{\|E^2\|}$$