11th US National Congress on Computational Mechanics:

# PolyTop: A Matlab implementation of a general topology optimization framework using unstructured polygonal finite element meshes

Ivan Menezes<sup>b</sup>, Cameron Talischi<sup>a</sup>, Anderson Pereira<sup>b</sup>, Glaucio H Paulino<sup>a</sup>

## <sup>*a*</sup>University of Illinois at Urbana-Champaign, USA <sup>*b*</sup>Tecgraf, Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Brazil

Minneapolis, Minnesota, July 26th, 2011



# Outline



- □ Problem formulation: regularization maps and interpolation functions
- □ Spatial discretization and the discrete optimization problem
- □ Modular framework: separation of formulation and analysis
- □ Code structure: inputs and implementation
- □ Demo, results and performance

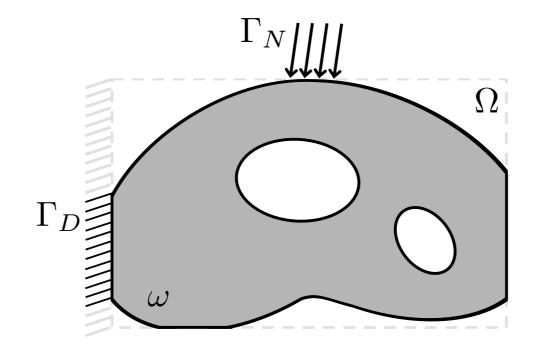
□ The topology optimization problem is of the form:

 $\inf_{\omega \in \mathcal{O}} f(\omega, \mathbf{u}_{\omega}) \quad \text{subject to} \quad g_i(\omega, \mathbf{u}_{\omega}) \le 0, \ i = 1, \dots, K$ 

where  $\mathbf{u}_{\omega}$  solves the boundary value problem:

$$\int_{\omega} \mathbf{C} \nabla \mathbf{u}_{\omega} : \nabla \mathbf{v} \mathrm{d} \mathbf{x} = \int_{\tilde{\Gamma}_N} \mathbf{t} \cdot \mathbf{v} \mathrm{d} s, \quad \forall \mathbf{v} \in \mathcal{V}_{\omega}$$

with  $\mathcal{V}_{\omega} = \left\{ \mathbf{v} \in H^1(\omega; \mathbb{R}^d) : \mathbf{v}|_{\partial \omega \cap \Gamma_D} = \mathbf{0} \right\}$ 



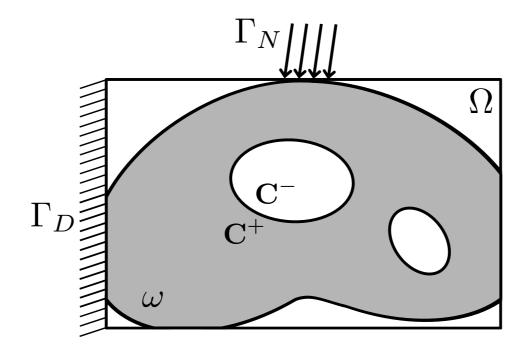
 $\Box$  The problem is reformulated as:

 $\inf_{\rho \in \mathcal{A}} f(\rho, \mathbf{u}_{\rho}) \qquad \text{subject to} \qquad g_i(\rho, \mathbf{u}_{\rho}) \le 0, \ i = 1, \dots, K$ 

where  $\mathcal{A} = \{\mathcal{P}(\eta) : \eta \in L^{\infty}(\Omega; [\underline{\rho}, \overline{\rho}])\}$  and the state equation is

$$\int_{\Omega} \boldsymbol{m}_{\boldsymbol{E}}(\rho) \mathbf{C} \nabla \mathbf{u}_{\rho} : \nabla \mathbf{v} d\mathbf{x} = \int_{\Gamma_N} \mathbf{t} \cdot \mathbf{v} ds, \quad \forall \mathbf{v} \in \mathcal{V}$$

with  $\mathcal{V} = \left\{ \mathbf{v} \in H^1(\Omega; \mathbb{R}^d) : \mathbf{v}|_{\Gamma_D} = \mathbf{0} \right\}$ 





 $\square$  We impose regularity on the space of admissible sizing function  $\mathcal{A}$  implicitly by means of "regularization" map  $\mathcal{P}$ , e.g.,

$$\mathcal{P}_F(\eta)(\mathbf{x}) := \int_{\Omega} F(\mathbf{x}, \overline{\mathbf{x}}) \eta(\overline{\mathbf{x}}) \mathrm{d}\overline{\mathbf{x}}$$

where F is a prescribed smooth kernel



 $\square$  We impose regularity on the space of admissible sizing function  $\mathcal{A}$  implicitly by means of "regularization" map  $\mathcal{P}$ , e.g.,

$$\mathcal{P}_F(\eta)(\mathbf{x}) := \int_{\Omega} F(\mathbf{x}, \overline{\mathbf{x}}) \eta(\overline{\mathbf{x}}) \mathrm{d}\overline{\mathbf{x}}$$

where F is a prescribed smooth kernel

- Even if  $\eta$  is rough,  $\rho = \mathcal{P}(\eta)$  is guaranteed to be smooth thereby eliminating the need to explicitly enforce regularity on  $\rho$
- $\circ~$  It is the discretization of  $\eta$  that produces the set of design variables for the optimization problem



□ We impose regularity on the space of admissible sizing function  $\mathcal{A}$  implicitly by means of "regularization" map  $\mathcal{P}$ , e.g.,

$$\mathcal{P}_F(\eta)(\mathbf{x}) := \int_{\Omega} F(\mathbf{x}, \overline{\mathbf{x}}) \eta(\overline{\mathbf{x}}) \mathrm{d}\overline{\mathbf{x}}$$

where F is a prescribed smooth kernel

- Even if  $\eta$  is rough,  $\rho = \mathcal{P}(\eta)$  is guaranteed to be smooth thereby eliminating the need to explicitly enforce regularity on  $\rho$
- $\circ~$  It is the discretization of  $\eta$  that produces the set of design variables for the optimization problem
- Other layout constraints such as symmetry can be achieved in the same way, for example,

$$\mathcal{P}_s(\eta)(\mathbf{x}) = \eta(x_1, |x_2|)$$

and these can be combined,  $\mathcal{P} = \mathcal{P}_F \circ \mathcal{P}_s$ 

□ Interpolation functions relate the sizing function to  $\rho$  to the material properties (e.g. stiffness and volume)

- □ Interpolation functions relate the sizing function to  $\rho$  to the material properties (e.g. stiffness and volume)
- □ Examples include

SIMP: 
$$m_E(\rho) = \varepsilon + (1 - \varepsilon)\rho^p$$
,  $m_V(\rho) = m_P(\rho) = \rho$   
RAMP:  $m_E(\rho) = \varepsilon + (1 - \varepsilon) \frac{\rho}{1 + q(1 - \rho)}$ ,  $m_V(\rho) = \rho$ 

- $\hfill\square$  Interpolation functions relate the sizing function to  $\rho$  to the material properties (e.g. stiffness and volume)
- □ Examples include

SIMP: 
$$m_E(\rho) = \varepsilon + (1 - \varepsilon)\rho^p$$
,  $m_V(\rho) = m_P(\rho) = \rho$   
RAMP:  $m_E(\rho) = \varepsilon + (1 - \varepsilon) \frac{\rho}{1 + q(1 - \rho)}$ ,  $m_V(\rho) = \rho$ 

□ "Nonlinear" filtering can also be cast in the same framework:

approach Guest et a.I (2004) is equivalent to defining  $m_E(\rho) = \varepsilon + (1 - \varepsilon) [H(\rho)]^p, \quad m_V(\rho) = H(\rho)$ 

where 
$$H(x) = 1 - \exp(-\beta x) + x \exp(-\beta)$$
 since  $\rho$  is already of the form  $\rho = \mathcal{P}_F(\eta)$ 

- Interpolation functions relate the sizing function to  $\rho$  to the material properties  $\square$ (e.g. stiffness and volume)
- **Examples include**  $\square$

 $\square$ 

SIMP: 
$$m_E(\rho) = \varepsilon + (1 - \varepsilon)\rho^p$$
,  $m_V(\rho) = m_P(\rho) = \rho$   
RAMP:  $m_E(\rho) = \varepsilon + (1 - \varepsilon) \frac{\rho}{1 + q(1 - \rho)}$ ,  $m_V(\rho) = \rho$ 

SIMP: 
$$m_E(\rho) = \varepsilon + (1 - \varepsilon)\rho^p$$
,  $m_V(\rho) = m_P(\rho) = \rho$   
RAMP:  $m_E(\rho) = \varepsilon + (1 - \varepsilon) \frac{\rho}{1 + q(1 - \rho)}$ ,  $m_V(\rho) = \rho$ 

"Nonlinear" filtering can also be cast in the same framework: for example, the

- □ Interpolation functions relate the sizing function to  $\rho$  to the material properties (e.g. stiffness and volume)
- Examples include

SIMP: 
$$m_E(\rho) = \varepsilon + (1 - \varepsilon)\rho^p$$
,  $m_V(\rho) = m_P(\rho) = \rho$   
RAMP:  $m_E(\rho) = \varepsilon + (1 - \varepsilon) \frac{\rho}{1 + q(1 - \rho)}$ ,  $m_V(\rho) = \rho$ 

"Nonlinear" filtering can also be cast in the same framework: for example, the approach Guest et a.I (2004) is equivalent to defining

$$m_E(\rho) = \varepsilon + (1 - \varepsilon) [H(\rho)]^p, \quad m_V(\rho) = H(\rho)$$

where  $H(x) = 1 - \exp(-\beta x) + x \exp(-\beta)$  since  $\rho$  is already of the form  $\rho = \mathcal{P}_F(\eta)$ 

• Observe fact that SIMP penalization plays a crucial role since with p = 1, we have  $m_E(\rho) \approx m_V(\rho)$  and so optimal solutions will consist mostly of "grey" no matter how large  $\beta$  is



## **Discretization**



 $\Box \text{ Consider } \mathcal{T}_h = \{\Omega_\ell\}_{\ell=1}^N \text{ a partition of } \Omega \text{ such that } \Omega_\ell \cap \Omega_k = \emptyset \text{ for } \ell \neq k \text{ and } \bigcup_\ell \overline{\Omega}_\ell = \overline{\Omega}$ 



- $\Box \text{ Consider } \mathcal{T}_h = \{\Omega_\ell\}_{\ell=1}^N \text{ a partition of } \Omega \text{ such that } \Omega_\ell \cap \Omega_k = \emptyset \text{ for } \ell \neq k \text{ and } \bigcup_\ell \overline{\Omega}_\ell = \overline{\Omega}$
- $\Box \quad \text{The discrete problem is the same optimization as before with } \mathcal{V} \text{ replaced by the finite element subspace } \mathcal{V}_h \text{ and } \mathcal{A} \text{ replaced by}$

$$\mathcal{A}_{h} = \left\{ \mathcal{P}_{h}(\eta_{h}) : \underline{\rho} \leq \eta_{h} \leq \overline{\rho}, \eta |_{\Omega_{\ell}} = \text{const } \forall \ell \right\}$$

where  $\mathcal{P}_h$  is an approximation to  $\mathcal{P}$ 



- $\Box \quad \text{Consider } \mathcal{T}_h = \{\Omega_\ell\}_{\ell=1}^N \text{ a partition of } \Omega \text{ such that } \Omega_\ell \cap \Omega_k = \emptyset \text{ for } \ell \neq k \text{ and } \bigcup_\ell \overline{\Omega}_\ell = \overline{\Omega}$
- $\Box \quad \text{The discrete problem is the same optimization as before with } \mathcal{V} \text{ replaced by the finite element subspace } \mathcal{V}_h \text{ and } \mathcal{A} \text{ replaced by}$

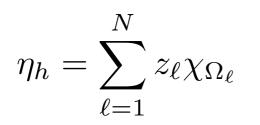
$$\mathcal{A}_{h} = \left\{ \mathcal{P}_{h}(\eta_{h}) : \underline{\rho} \leq \eta_{h} \leq \overline{\rho}, \eta|_{\Omega_{\ell}} = \text{const } \forall \ell \right\}$$

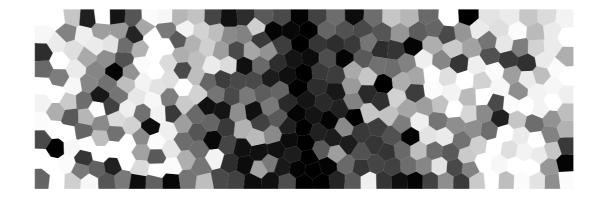
where  $\mathcal{P}_h$  is an approximation to  $\mathcal{P}$ 

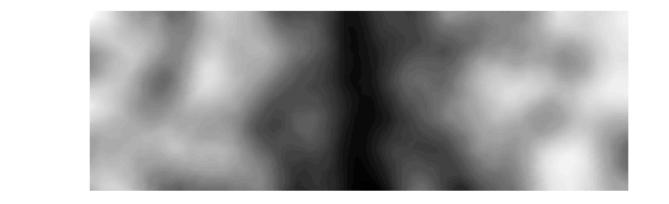
□ Each piecewise constant  $\eta_h$  can be represented by vector  $\mathbf{z} = [z_\ell]$  since  $\eta_h(\mathbf{x}) = \sum_{\ell=1}^N z_\ell \chi_{\Omega_\ell}(\mathbf{x})$  and similarly each  $\rho_h \in \mathcal{A}_h$  can be defined by elemental values  $\mathbf{y} = \mathbf{P}\mathbf{z}$  where

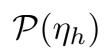
$$(\mathbf{P})_{\ell k} = \mathcal{P}(\chi_{\Omega_k})(\mathbf{x}_{\ell}^*)$$

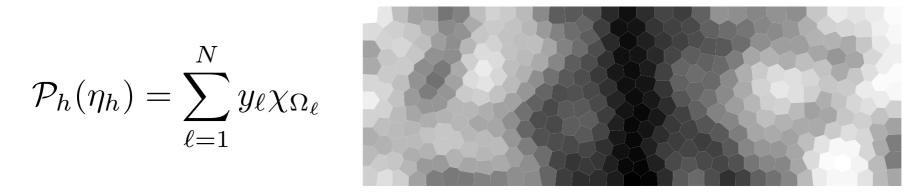














 $\Box$  For the minimum compliance problem,  $\mathbf{E} := m_E(\mathbf{Pz})$  and  $\mathbf{V} := m_V(\mathbf{Pz})$  are the only design related information that need to be provided to the analysis functions



- $\Box$  For the minimum compliance problem,  $\mathbf{E} := m_E(\mathbf{Pz})$  and  $\mathbf{V} := m_V(\mathbf{Pz})$  are the only design related information that need to be provided to the analysis functions
  - $\circ~$  The analysis functions need not know about the choice of interpolations functions or the mapping  ${\cal P}$
  - A clear advantage of this approach is that the analysis functions can be extended, developed and modified independently



- $\Box$  For the minimum compliance problem,  $\mathbf{E} := m_E(\mathbf{Pz})$  and  $\mathbf{V} := m_V(\mathbf{Pz})$  are the only design related information that need to be provided to the analysis functions
  - $\circ~$  The analysis functions need not know about the choice of interpolations functions or the mapping  ${\cal P}$
  - A clear advantage of this approach is that the analysis functions can be extended, developed and modified independently
- □ The sensitivity analysis can be "separated" along the same lines:

$$\frac{\partial g_i}{\partial \mathbf{z}} = \frac{\partial \mathbf{E}}{\partial \mathbf{z}} \frac{\partial g_i}{\partial \mathbf{E}} + \frac{\partial \mathbf{V}}{\partial \mathbf{z}} \frac{\partial g_i}{\partial \mathbf{V}}$$

where  $\partial g_i / \partial \mathbf{E}$  and  $\partial g_i / \partial \mathbf{V}$  are sensitivities with respect to analysis parameters and

$$\frac{\partial \mathbf{E}}{\partial \mathbf{z}} = \mathbf{P}^T J_{m_E}(\mathbf{P}\mathbf{z}), \qquad \frac{\partial \mathbf{V}}{\partial \mathbf{z}} = \mathbf{P}^T J_{m_V}(\mathbf{P}\mathbf{z})$$



- $\Box$  For the minimum compliance problem,  $\mathbf{E} := m_E(\mathbf{Pz})$  and  $\mathbf{V} := m_V(\mathbf{Pz})$  are the only design related information that need to be provided to the analysis functions
  - $\circ~$  The analysis functions need not know about the choice of interpolations functions or the mapping  ${\cal P}$
  - A clear advantage of this approach is that the analysis functions can be extended, developed and modified independently
- □ The sensitivity analysis can be "separated" along the same lines:

$$\frac{\partial g_i}{\partial \mathbf{z}} = \frac{\partial \mathbf{E}}{\partial \mathbf{z}} \frac{\partial g_i}{\partial \mathbf{E}} + \frac{\partial \mathbf{V}}{\partial \mathbf{z}} \frac{\partial g_i}{\partial \mathbf{V}}$$

where  $\partial g_i / \partial \mathbf{E}$  and  $\partial g_i / \partial \mathbf{V}$  are sensitivities with respect to analysis parameters and

$$\frac{\partial \mathbf{E}}{\partial \mathbf{z}} = \mathbf{P}^T J_{m_E}(\mathbf{P}\mathbf{z}), \qquad \frac{\partial \mathbf{V}}{\partial \mathbf{z}} = \mathbf{P}^T J_{m_V}(\mathbf{P}\mathbf{z})$$

□ The optimizer should also be kept separate but this is more common



□ The input to the main kernel PolyTop consists of two Matlab structure arrays containing the optimization and analysis fields:

fem	opt			
fem.NNode	opt.zMin			
fem.NElem	opt.zMax			
fem.Node	opt.zIni			
fem.Element	opt.MatIntFnc			
fem.Supp	opt.P			
fem.Load	opt.MaxIter			
fem.ShapeFnc	opt.Tol			



□ The input to the main kernel PolyTop consists of two Matlab structure arrays containing the optimization and analysis fields:

fem	opt
fem.NNode	opt.zMin
fem.NElem	opt.zMax
fem.Node	opt.zIni
fem.Element	opt.MatIntFnc
fem.Supp	opt.P
fem.Load	opt.MaxIter
fem.ShapeFnc	opt.Tol

 $\Box$  Given an input vector y, MatIntFnc function returns arrays  $\mathbf{E} = m_E(\mathbf{y})$  and  $\mathbf{V} = m_V(\mathbf{y})$  and the sensitivity vectors  $\partial \mathbf{E} / \partial \mathbf{y} := m'_E(\mathbf{y})$  and  $\partial \mathbf{V} / \partial \mathbf{y} := m'_V(\mathbf{y})$ 



PolyTop possesses fewer than 190 lines, of which 116 lines pertain to the finite element analysis including 81 lines for the element stiffness calculations for polygonal elements



PolyTop possesses fewer than 190 lines, of which 116 lines pertain to the finite element analysis including 81 lines for the element stiffness calculations for polygonal elements

```
7 function [z,V,fem] = PolyTop(fem,opt)
  Iter=0; Tol=opt.Tol*(opt.zMax-opt.zMin); Change=2*Tol; z=opt.zIni; P=opt.P;
8
  [E, dEdy, V, dVdy] = opt.MatIntFnc(P*z);
9
  [FigHandle,FigData] = InitialPlot(fem,z);
10
  while (Iter<opt.MaxIter) && (Change>Tol)
11
    Iter = Iter + 1;
12
   %Compute cost functionals and analysis sensitivities
13
    [f,dfdE,dfdV,fem] = ObjectiveFnc(fem,E,V);
14
    [g,dgdE,dgdV,fem] = ConstraintFnc(fem,E,V,opt.VolFrac);
15
    %Compute design sensitivities
16
    dfdz = P' * (dEdy. * dfdE + dVdy. * dfdV);
17
    dqdz = P' * (dEdy. * dqdE + dVdy. * dqdV);
18
    %Update design variable and analysis parameters
19
    [z,Change] = UpdateScheme(dfdz,g,dgdz,z,opt);
20
    [E, dEdy, V, dVdy] = opt.MatIntFnc(P*z);
21
    %Output results
22
    fprintf('It: %i \t Objective: %1.3f\tChange: %1.3f\n',Iter,f,Change);
23
    set(FigHandle, 'FaceColor', 'flat', 'CData', 1-V(FigData)); drawnow
24
  end
25
```

Certain quantities used in the analysis functions such as element stiffness matrices as well as the connectivity of the global stiffness matrix K need to be computed only once

- Certain quantities used in the analysis functions such as element stiffness matrices as well as the connectivity of the global stiffness matrix K need to be computed only once
- This is accomplished in PolyTop by computing vector fem.i, fem.j, fem.k and fem.e with assembly computed by command:

K = sparse(fem.i,fem.j,E(fem.e).\*fem.k);

- Certain quantities used in the analysis functions such as element stiffness matrices as well as the connectivity of the global stiffness matrix K need to be computed only once
- This is accomplished in PolyTop by computing vector fem.i, fem.j, fem.k and fem.e with assembly computed by command:

K = sparse(fem.i,fem.j,E(fem.e).\*fem.k);

- □ The isoparametric polygonal elements can be viewed as extension of the common linear triangles and bilinear quads to all convex *n*-gons
  - This element stiffness calculations add very little overhead

□ Matlab demo





#### □ Matlab demo

□ Comparison of efficiency with 88 line:

mesh size	$90 \times 30$	$150 \times 50$	$300 \times 100$	$600 \times 200$
total time of PolyTop	15.5	40.7	187	1016
total time of 88 line	14.8	44.4	360	4463

### Matlab demo

□ Comparison of efficiency with 88 line:

mesh size	$90 \times 30$	$150 \times 50$	$300 \times 100$	$600 \times 200$
total time of PolyTop	15.5	40.7	187	1016
total time of 88 line	14.8	44.4	360	4463

Source of discrepancy is the computation of volume constraint inside the OC optimizer:

$$V(\mathbf{z}) = \sum_{\ell=1}^{N} (\mathbf{P}\mathbf{z})_{\ell} = \mathbf{1}^{T} (\mathbf{P}\mathbf{z}) = (\mathbf{1}^{T}\mathbf{P}) \mathbf{z} = (\mathbf{P}^{T}\mathbf{1})^{T} \mathbf{z}$$

 Though the above expression is not explicitly used in PolyTop, the decoupling of the OC scheme from the analysis routine naturally leads to the more efficient calculation



- We have a general framework for topology optimization using unstructured meshes in arbitrary domains
- □ The analysis routine and optimization algorithm are separated from the specific choice of topology optimization formulation
- The FE and sensitivity analysis routines can be extended, maintained, developed, and/or modified independently

QUESTIONS?