

Macaron/Tonus retreat presentation

Mesh-based methods and physically informed learning

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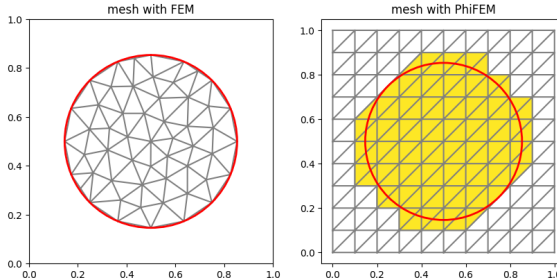
Introduction

Scientific context

Context : Create real-time digital twins of an organ (such as the liver).

ϕ -FEM Method : New fictitious domain finite element method.

- domain given by a level-set function \Rightarrow don't require a mesh fitting the boundary
- allow to work on complex geometries
- ensure geometric quality



Practical case: Real-time simulation, shape optimization...

Objective

Current Objective : Develop hybrid finite element / neural network methods.

OFFLINE :

Several Geometries



+

Several Functions



Train a PINNs



ONLINE :

1 Geometry - 1 Function



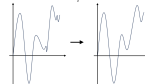
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Get PINNs prediction



Correct prediction with ϕ -FEM



Evolution :

- Geometry : 2D, simple, fixed (as circle, ellipse..) \rightarrow 3D / complex / variable
- PDE : simple, static (Poisson problem) \rightarrow complex / dynamic (elasticity, hyper-elasticity)
- Neural Network : simple and defined everywhere (PINNs) \rightarrow Neural Operator

Problem considered

Elliptic problem with Dirichlet conditions :

Find $u : \Omega \rightarrow \mathbb{R}^d (d = 1, 2, 3)$ such that

$$\begin{cases} L(u) = -\nabla \cdot (A(x)\nabla u(x)) + c(x)u(x) = f(x) & \text{in } \Omega, \\ u(x) = g(x) & \text{on } \partial\Omega \end{cases} \quad (1)$$

with A a definite positive coercivity condition and c a scalar. We consider Δ the Laplace operator, Ω a smooth bounded open set and Γ its boundary.

Weak formulation :

Find $u \in V$ such that $a(u, v) = l(v) \forall v \in V$

with

$$\begin{aligned} a(u, v) &= \int_{\Omega} (A(x)\nabla u(x)) \cdot \nabla v(x) + c(x)u(x)v(x) \, dx \\ l(v) &= \int_{\Omega} f(x)v(x) \, dx \end{aligned}$$

Remark : For simplicity, we will not consider 1st order terms.

Numerical methods

Objective : Show that the philosophy behind most of the methods are the same.

Mesh-based methods // Physically informed learning

Numerical methods : Discretize an infinite-dimensional problem (unknown = function) and solve it in a finite-dimensional space (unknown = vector).

- **Encoding :** we encode the problem in a finite-dimensional space
- **Approximation :** solve the problem in finite-dimensional space
- **Decoding :** bring the solution back into infinite dimensional space

Encoding	Approximation	Decoding
$f \rightarrow \theta_f$	$\theta_f \rightarrow \theta_u$	$\theta_u \rightarrow u_\theta$

Mesh-based methods

Encoding/Decoding
Approximation

Mesh-based methods

Encoding/Decoding

Approximation

Encoding/Decoding - FEMs

- **Decoding** : Linear combination of piecewise polynomial function φ_i .

$$\mathcal{D}_{\theta_u}(x) = \sum_{i=1}^N (\theta_u)_i \varphi_i$$

\Rightarrow linear decoding \Rightarrow approximation space $V_N =$ vectorial space

\Rightarrow existence and uniqueness of the orthogonal projector

- **Encoding** : Orthogonal projection on vector space $V_N = \text{Vect}\{\varphi_1, \dots, \varphi_N\}$.

$$\theta_f = E(f) = M^{-1}b(f)$$

with $M_{ij} = \int_{\Omega} \varphi_i(x) \varphi_j(x)$ and $b_i(f) = \int_{\Omega} \varphi_i(x) f(x)$. Appendix 1

Mesh-based methods

Encoding/Decoding

Approximation

Approximation

Idea : Project a certain form of the equation onto the vector space V_N .
We introduce the residual of the equation defined by

$$R(v) = R_{in}(v)\mathbb{1}_{\Omega} + R_{bc}(v)\mathbb{1}_{\partial\Omega}$$

with

$$R_{in}(v) = L(v) - f \quad \text{and} \quad R_{bc}(v) = v - g$$

which respectively define the residues inside Ω and on the boundary $\partial\Omega$.

Discretization : Degrees of freedom problem (which also has a unique solution)

$$u = \arg \min_{v \in V_N} J(v) \quad \longrightarrow \quad \theta_u = \arg \min_{\theta \in \mathbb{R}^N} J(\theta)$$

with J a functional to minimize.

Variants : Depends on the problem form used for projection.

Problem - Energetic form
Galerkin projection

Problem - Least-square form
Galerkin Least-square projection

Energetic form

Minimization Problem :

$$u_\theta(x) = \arg \min_{v \in V_N} J(v), \quad J(v) = J_{in}(v) + J_{bc}(v) \quad (2)$$

with

$$J_{in}(v) = \frac{1}{2} \int_{\Omega} L(v)v - \int_{\Omega} f v \quad \text{et} \quad J_{bc}(v) = \frac{1}{2} \int_{\Omega} R_{bc}(v)^2$$

Remark : This form of the problem is due to the Lax-Milgram theorem as a is symmetrical.

Minimization Problem (2) \Leftrightarrow PDE (1) :

$$\nabla_v J(v) = R(v)$$

Appendix 2

$$\begin{array}{ccc} u_\theta \text{ sol} & \Leftrightarrow \nabla_{u_\theta} J(u_\theta) = 0 \Leftrightarrow \begin{cases} R_{in}(u_\theta) = 0 \text{ in } \Omega \\ u_\theta = g \text{ on } \partial\Omega \end{cases} \Leftrightarrow & u_\theta \text{ sol} \\ \text{of (2)} & & \text{of (1)} \end{array}$$

Min pb

PDE

Galerkin Projection

Discrete minimization Problem :

$$\theta_u = \arg \min_{\theta \in \mathbb{R}^N} J(\theta), \quad J(\theta) = J_{in}(\theta) = \frac{1}{2} \int_{\Omega} L(u_{\theta}) v_{\theta} - \int_{\Omega} f v_{\theta} \tag{3}$$

Remark : In practice, boundary conditions can be imposed in different ways. We are therefore only interested in the minimization problem in Ω .

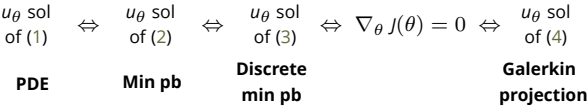
Galerkin projection : Consists in resolving

$$\langle R_{in}(u_{\theta}(x)), \varphi_i \rangle_{L^2} = 0, \quad \forall i \in \{1, \dots, N\} \tag{4}$$

Galerkin Projection (4) \Leftrightarrow PDE (1) :

$$\nabla_{\theta} J(\theta) = \left(\int_{\Omega} R_{in}(v_{\theta}) \varphi_i \right)_{i=1, \dots, N}$$

Appendix 3



Least-Square form

Minimization Problem :

$$u_{\theta}(x) = \arg \min_{v \in V_N} J(v), \quad J(v) = J_{in}(v) + J_{bc}(v) \quad (5)$$

with

$$J_{in}(v) = \frac{1}{2} \int_{\Omega} R_{in}(v)^2 \quad \text{and} \quad J_{bc}(v) = \frac{1}{2} \int_{\Omega} R_{bc}(v)^2$$

Remark : This form of the problem is due to the Lax-Milgram theorem as a is symmetrical.

Minimization Problem (5) \Leftrightarrow PDE (1) :

$$\nabla_v J(v) = L(R(v)) \mathbb{1}_{\Omega} + (v - g) \mathbb{1}_{\partial\Omega}$$

Appendix 4

$$u_{\theta} \text{ sol of (5)} \Leftrightarrow \nabla_{u_{\theta}} J(u_{\theta}) = 0 \Leftrightarrow \begin{cases} L(R(u_{\theta})) = 0 \text{ in } \Omega \\ R(u_{\theta}) = 0 \text{ on } \partial\Omega \end{cases} \Leftrightarrow R(u_{\theta}) = 0 \Leftrightarrow u_{\theta} \text{ sol of (1)}$$

Min pb

PDE

A modifier !

Least-Square Galerkin Projection

Discrete minimization Problem :

$$\theta_u = \arg \min_{\theta \in \mathbb{R}^N} J(\theta), \quad J(\theta) = J_{in}(\theta) = \frac{1}{2} \int_{\Omega} (L(u_{\theta}) - f)^2 \tag{6}$$

Remark : In practice, boundary conditions can be imposed in different ways. We are therefore only interested in the minimization problem in Ω .

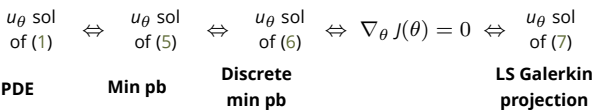
Galerkin projection : Consists in resolving

$$\langle R_{in}(u_{\theta}(x)), (\nabla_{\theta} R_{in}(u_{\theta}(x)))_i \rangle_{L^2} = 0, \quad \forall i \in \{1, \dots, N\} \tag{7}$$

Least-Square Galerkin Projection (7) \Leftrightarrow PDE (1) :

$$\nabla_{\theta} J(\theta) = \left(\int_{\Omega} L(R_{in}(v_{\theta})) \varphi_i \right)_{i=1, \dots, N}$$

Appendix 5



Steps Decomposition - FEMs

Encoding	Approximation		Decoding
$f \rightarrow \theta_f$	$\theta_f \rightarrow \theta_u$		$\theta_u \rightarrow u_\theta$
$\theta_f = \mathcal{E}(f)$ $= M^{-1}b(f)$	Galerkin	LS Galerkin	$u_\theta(x) = \mathcal{D}_\theta(x)$ $= \sum_{i=1}^N (\theta_u)_i \varphi_i$
	$\langle R(u_\theta), \varphi_i \rangle_{L^2} = 0$	$\langle R(u_\theta), (\nabla_\theta R(u_\theta))_i \rangle_{L^2} = 0$	
	$A\theta_u = B$		

Example : Galerkin projection.
 For $i \in \{1, \dots, N\}$,

$$\begin{aligned} &\langle R(u_\theta), \varphi_i \rangle_{L^2} = 0 \\ \iff &\int_{\Omega} L(u_\theta) \varphi_i = \int_{\Omega} f \varphi_i \\ \iff &\sum_{j=1}^N (\theta_u)_j \int_{\Omega} \varphi_i L(\varphi_j) = \int_{\Omega} f \varphi_i \end{aligned}$$

$$\begin{aligned} &A\theta_u = B \text{ with} \\ A_{i,j} = \int_{\Omega} \varphi_i L(\varphi_j) \quad , \quad B_i = \int_{\Omega} f \varphi_i \end{aligned}$$

Physically Informed Learning

Encoding/Decoding
Approximation

Physically Informed Learning

Encoding/Decoding

Approximation

Encoding/Decoding - NNs

A compléter !

Non-Linear Decoder - Advantages

A compléter !

Physically Informed Learning

Encoding/Decoding

Approximation

Approximation

A compléter !

Deep-Ritz

A compléter !

Standard PINNs

A compléter !

In practice...

A compléter !

Steps Decomposition - NNs

Encoding	Approximation		Decoding
$f \rightarrow \theta_f$	$\theta_f \rightarrow \theta_u$		$\theta_u \rightarrow u_\theta$
$\theta_f = \mathcal{E}(f)$ $= M^{-1}b(f)$	Galerkin	LS Galerkin	$u_\theta(x) = \mathcal{D}_\theta(x)$ $= \sum_{i=1}^N (\theta_u)_i \varphi_i$
	$\langle R(u_\theta), \varphi_i \rangle_{L^2} = 0$	$\langle R(u_\theta), (\nabla_\theta R(u_\theta))_i \rangle_{L^2} = 0$ $A\theta_u = B$	

A compléter !

Hybrid method

ϕ -FEM Method

A compléter !

Impose exact boundary conditions in PINNs

A compléter !

Correct PINNs prediction with ϕ FEM

A compléter !

Conclusion

Conclusion

A compléter !

Bibliography

Bibliography

Appendix 1 : Encoding - FEMs

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Appendix 2 : Energetic form

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Appendix 3 : Galerkin Projection

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Appendix 4 : Least-Square form

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Appendix 5 : LS Galerkin Projection

A compléter !