

Tuning effective dynamical properties of periodic media by FFT-accelerated topological optimization

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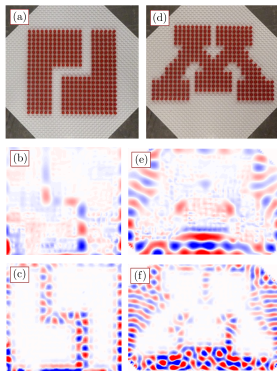
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Control of wave propagation using periodic structures

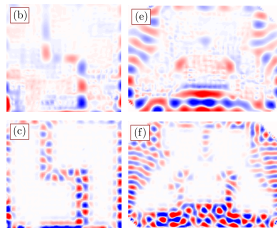
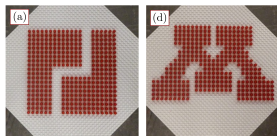
... to design waveguides

- with resonators for long wavelengths / low frequencies
- with Bragg effects for medium wavelengths / frequencies



[Celli and Gonella, 2015]

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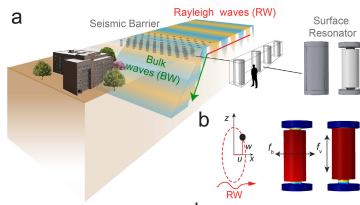


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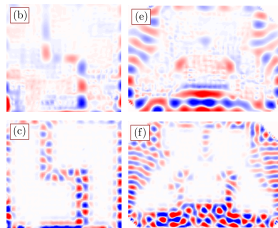
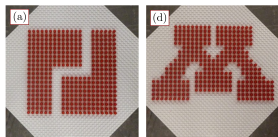
... to design seismic protections (with resonators)



[Palermo et al., 2016]

... and more (negative effective properties, cloaking ...)

Control of wave propagation using periodic structures

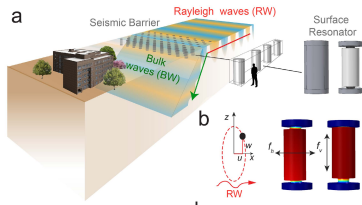


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How to obtain desired properties ?

- Known design (cylinders, spheres, cones, LEGO bricks ...) \implies *parameter optimization* [Huang et al., 2016, Palermo et al., 2016] ...
- Given materials, unknown design \implies *topological optimization* [Vondřejc et al., 2017, Kook and Jensen, 2017, Allaire and Yamada, 2018] ...

This work: topological optimization of *dispersive properties* (long wavelengths, no resonances)

Outline

1 Introduction

2 Optimization problem and modeling tools

- Dispersive model obtained by second-order homogenization
- Optimization problem
- Topological derivatives: sensitivity to a phase change
- FFT-based algorithm to solve cell problems

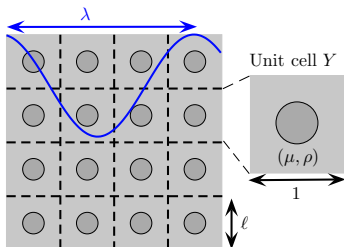
3 Optimization algorithm and examples

- Pixel-by-pixel approach
- Level-set representation of the unit cell and projection algorithm
- Fitting an objective phase velocity

4 Conclusions and perspectives

Second-order homogenization for waves in a periodic medium

[Bensoussan et al., 1978, Boutin and Auriault, 1993, Andrianov et al., 2008, Wautier and Guzina, 2015] ...



- Antiplane shear waves in the time-harmonic regime:

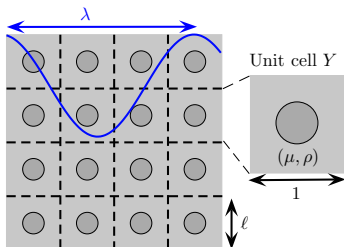
$$\operatorname{div} \left[\mu \left(\frac{\mathbf{x}}{\ell} \right) \nabla u_\ell \right] + \rho \left(\frac{\mathbf{x}}{\ell} \right) \omega^2 u_\ell = 0$$

- (μ, ρ) : Y -periodic shear modulus and density
- Two-scale expansion for *long wavelengths* $\lambda > \ell$:

$$u_\ell(\mathbf{x}) = \underbrace{U(\mathbf{x})}_{\text{mean field}} + \underbrace{\ell \nabla U(\mathbf{x}) \cdot \mathbf{P}(\mathbf{x}/\ell)}_{\text{oscillatory correctors}} + \dots$$

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Second-order homogenized equation for the mean field U :

$$\left[\boldsymbol{\mu}_0 + \ell^2 \boldsymbol{\mu}_2 : \nabla^2 \right] : \nabla^2 U + \omega^2 \left[\varrho_0 + \ell^2 \boldsymbol{\varrho}_2 : \nabla^2 \right] U = 0$$

$(\boldsymbol{\mu}_0, \varrho_0, \boldsymbol{\mu}_2, \boldsymbol{\varrho}_2)$: constant *tensors* obtained from *cell solutions* $(\mathbf{P}, \mathbf{Q}, \mathbf{R})$:

$$(Y, \mu, \rho) \implies \begin{cases} \mathbf{P} = (P_1, P_2) \\ \mathbf{Q} = (Q_{11}, Q_{12}, Q_{22}) \\ \mathbf{R} = (R_{111}, R_{112}, R_{122}, R_{222}) \end{cases} \implies \begin{cases} \varrho_0 = \langle \rho \rangle = \text{mean of } \rho \text{ on } Y \\ \boldsymbol{\mu}_0 = \langle \mu(\mathbf{I} + \nabla \mathbf{P}) \rangle \\ \boldsymbol{\varrho}_2 = \langle \rho \mathbf{Q} \rangle \\ \boldsymbol{\mu}_2 = \langle \mu(\mathbf{I} \otimes \mathbf{Q} + \nabla \mathbf{R}) \rangle \end{cases}$$

Approximation of dispersion

- Plane wave mean field $U(x, t) = \exp [i(k\mathbf{d} \cdot \mathbf{x} - \omega t)] \implies$ *dispersion relation* $\omega = \omega(k, \mathbf{d})$.
- *Phase velocity* for the second-order homogenized model:

$$\begin{aligned} c(k, \mathbf{d}) = \frac{\omega(k, \mathbf{d})}{k} &= \underbrace{c_0(\mathbf{d})}_{\text{limit velocity}} + \underbrace{\Delta c(k, \mathbf{d})}_{\text{dispersion}} \\ &= c_0(\mathbf{d}) + \frac{1}{2} \frac{\gamma(\mathbf{d})}{c_0(\mathbf{d})} (k\ell)^2 + o((k\ell)^2) \quad \text{as } k\ell \sim \frac{\ell}{\lambda} \rightarrow 0 \end{aligned}$$

$$c_0(\mathbf{d}) = \sqrt{\frac{\mu_0}{\varrho_0} : (\mathbf{d} \otimes \mathbf{d})} \quad \text{and} \quad \gamma(\mathbf{d}) = \left[\frac{\varrho_2 \otimes \mu_0 - \varrho_0 \mu_2}{(\varrho_0)^2} \right] :: (\mathbf{d} \otimes \mathbf{d} \otimes \mathbf{d} \otimes \mathbf{d})$$

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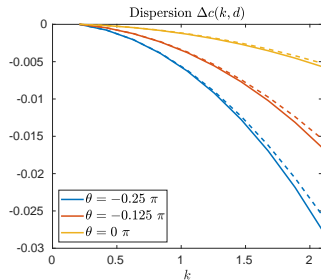
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$\mu = 7$ $\rho = 1.2$	$\mu = 1$ $\rho = 1$
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$c_0(\mathbf{d}) \approx 1.55$ (isotropic)



Cost functionals and optimization problem

- Given given N_θ directions $(\mathbf{d}_1, \dots, \mathbf{d}_{N_\theta})$ of interest, a *cost functional* \mathcal{J} can be defined as:

$$\mathcal{J}(\mu, \rho) = J(c_0(\mathbf{d}_1), \dots, c_0(\mathbf{d}_{N_\theta}); \gamma(\mathbf{d}_1), \dots, \gamma(\mathbf{d}_{N_\theta}))$$

- Example:** to minimize $|\gamma(\mathbf{d}^-)|$ and maximize $|\gamma(\mathbf{d}^+)|$:

$$\mathcal{J}(\mu, \rho) = \frac{1}{2} \left[[\gamma(\mathbf{d}^-)]^2 + \frac{1}{[\gamma(\mathbf{d}^+)]^2} \right]$$

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Topological optimization problem

Find the distribution of (μ, ρ) in Y that minimizes $\mathcal{J}(\mu, \rho)$, with

- the dependencies $(\mu, \rho) \rightarrow (\mathbf{P}, \mathbf{Q}, \mathbf{R}) \rightarrow (\varrho_0, \boldsymbol{\mu}_0, \varrho_2, \boldsymbol{\mu}_2) \rightarrow \{c_0(\mathbf{d}_j), \gamma(\mathbf{d}_j)\}_{j=1..N_\theta} \rightarrow \mathcal{J}$
- Constraints / parametrization of (μ, ρ) (to simplify the problem)

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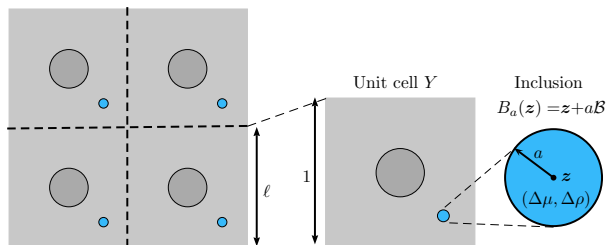
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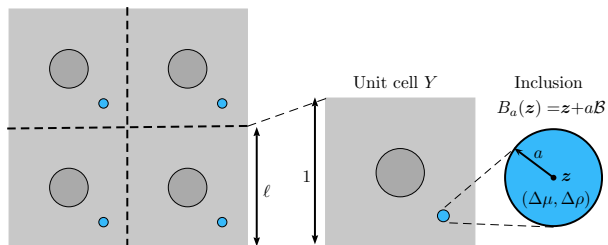
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- Matrix and inclusions, inclusion shape parametrization and shape sensitivity
[Vondřejc et al., 2017]
- Two-phase material, *level-set* description of the interface and shape sensitivity
[Allaire and Yamada, 2018]
- Two-phase material and **topological derivative** to quantify the effects of a phase change
[Amstutz, 2011, Oliver et al., 2018] (optimization of *static properties of microstructures*)

Topological derivative of a cost functional



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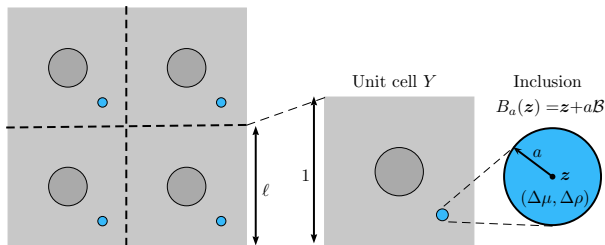


- Phase change in the unit cell: $(\mu, \rho) \rightarrow (\mu_a, \rho_a) = (\mu, \rho) + \chi_{B_a}(\Delta\mu, \Delta\rho)$
- Expansion of \mathcal{J} :

$$\mathcal{J}(\mu_a, \rho_a) = \mathcal{J}(\mu, \rho) + a^2 \mathcal{D}\mathcal{J} + o(a^2) \quad \text{as } a \rightarrow 0$$

- $\mathcal{D}\mathcal{J}(\mu, \rho; \mathbf{z}, \mathcal{B}, \Delta\mu, \Delta\rho)$ is the *topological derivative* (or gradient, or sensitivity) of \mathcal{J} .
[Sokolowski and Zochowski, 1999, Garreau et al., 2001, Amstutz, 2011, Bonnet et al., 2018] ...

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- Chain rule when $\mathcal{J}(\mu, \rho) = J(\varrho_0, \boldsymbol{\mu}_0, \varrho_2, \boldsymbol{\mu}_2)$:

$$\mathcal{D}\mathcal{J} = \frac{\partial J}{\partial \varrho_0} \mathcal{D}\varrho_0 + \frac{\partial J}{\partial \boldsymbol{\mu}_0} : \mathcal{D}\boldsymbol{\mu}_0 + \frac{\partial J}{\partial \varrho_2} \mathcal{D}\varrho_2 + \frac{\partial J}{\partial \boldsymbol{\mu}_2} :: \mathcal{D}\boldsymbol{\mu}_2.$$

Cell problems and FFT-based algorithm

Computing $(\mathcal{D}\varrho_0, \mathcal{D}\mu_0, \mathcal{D}\varrho_2, \mathcal{D}\mu_2)$ requires the resolution of:

$$\left. \begin{array}{l} 3 \text{ cell problems } P, Q, R \\ 2 \text{ adjoint cell problems } \beta \text{ and } \mathbf{X}[\beta] \end{array} \right\} 12 \text{ scalar cell problems}$$

[Bonnet, Cornaggia, Guzina, SIAP 2018]

All cell problems are *static equilibrium problems*: for $\chi = P, Q, R, \beta$ or $\mathbf{X}[\beta]$,

$$\left\{ \begin{array}{l} \nabla \cdot [\mu(\mathbf{E} + \nabla\chi)] + \mathbf{f} = \mathbf{0} \quad \text{in } Y, \\ \chi \text{ is } Y\text{-periodic,} \\ \langle \chi \rangle = 0, \end{array} \right.$$

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Numerical resolution:

- Finite elements (FreeFem++, Comsol, Fenics, Xlife++ ...)
- FFT-based methods [Moulinec and Suquet, 1998, Moulinec et al., 2018]
 - ▶ Problem reformulation: Lippmann-Schwinger integral equation involving a *reference material*
 - ▶ Fixed-point algorithm
 - ▶ Extensive use of FFT to compute convolution products
 - ▶ **Discretisation of the cell on pixels**

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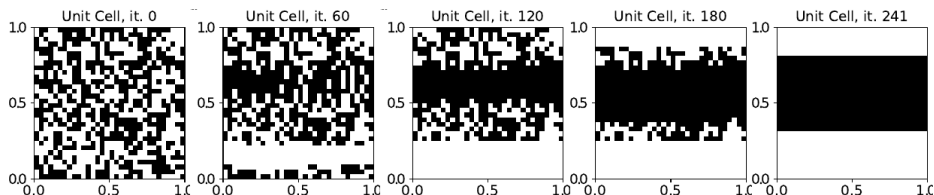
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Pixel-by-pixel two-directions optimization

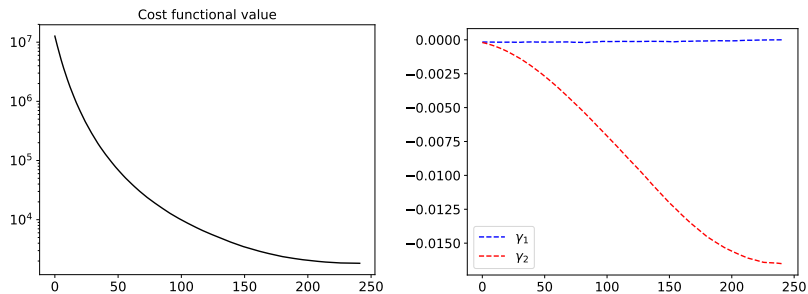
- Directions of interest $\mathbf{d}^- = \mathbf{e}_1$ (horizontal), $\mathbf{d}^+ = \mathbf{e}_2$ (vertical).

$$\mathcal{J}(\mu, \rho) = \frac{1}{2} \left[[\gamma(\mathbf{d}^-)]^2 + \frac{1}{[\gamma(\mathbf{d}^+)]^2} \right]$$

- Two-phase unit cell: $Y = Y_1 \cup Y_2$, with:
 - ▶ material ratios $\rho_2 = 2\rho_1$ and $\mu_2 = 2\mu_1 \Rightarrow$ uniform wavespeed
 - ▶ equal phase ratio: $|Y_1| = |Y_2|$
- Pixel-by-pixel algorithm:
 - ▶ Initialize material repartition (Y_1, Y_2) with $|Y_1| = |Y_2|$
 - ▶ While $(\min_{Y_1} \mathcal{D}\mathcal{J} + \min_{Y_2} \mathcal{D}\mathcal{J}) < 0$, exchange the two pixels where the minima are reached
 - ▶ $|Y_1| = |Y_2|$ is automatically respected



Pixel-by-pixel two-directions optimization - cost functional and dispersions



Computational remarks:

- 241 iterations
- 1205 cell and adjoint cell problems i.e. **2892 scalar cell problems** on a 32×32 grid
- Moulinec-Suquet FFT method (tolerance on relative residual error: 10^{-8}) implemented using Python.

$\implies \approx 15$ -20s on a (good) laptop.

Level-set representation and projection algorithm

[Amstutz and Andrä, 2006, Amstutz, 2011]

- Material distribution at iteration n represented by a **level-set function** ψ^n :

$$(\star) \begin{cases} \psi^n > 0 & \text{in } Y_1 \\ \psi^n < 0 & \text{in } Y_2 \end{cases} \quad \text{and} \quad \|\psi^n\|_{L^2(Y)} = 1$$

- Signed and normalized TD $\overline{\mathcal{D}\mathcal{J}}$:

$$\tilde{\mathcal{D}\mathcal{J}} := \begin{cases} \mathcal{D}\mathcal{J} & \text{in } Y_1 \\ -\mathcal{D}\mathcal{J} & \text{in } Y_2 \end{cases} \quad \text{and} \quad \overline{\mathcal{D}\mathcal{J}} := \frac{\tilde{\mathcal{D}\mathcal{J}}}{\|\tilde{\mathcal{D}\mathcal{J}}\|_{L^2(Y)}}$$

- Optimality condition:

If $\overline{\mathcal{D}\mathcal{J}}$ satisfies the sign condition (\star) then $\mathcal{D}\mathcal{J}(z) > 0 \quad \forall z \in Y$
then \mathcal{J} reached a *local minimum*

In particular, it is true if $\psi^N = \overline{\mathcal{D}\mathcal{J}}(\psi^N)$ for some iteration N .

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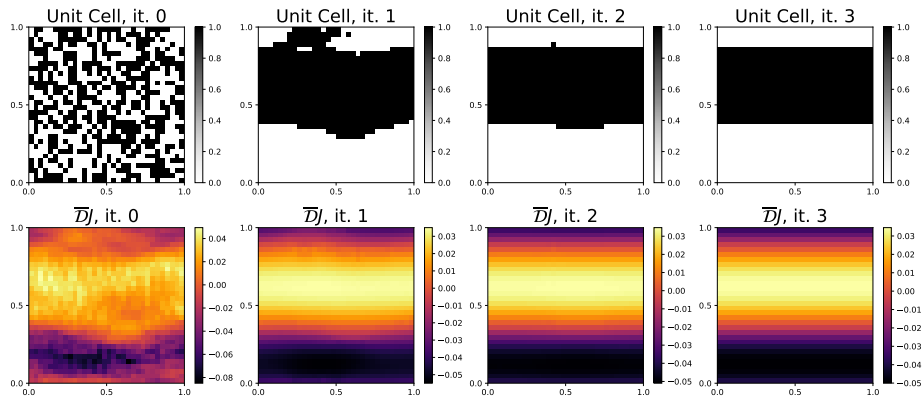
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Update of ψ by *projection* onto $\overline{\mathcal{D}\mathcal{J}}$:

$$\psi^{n+1} = a_n \psi^n + b_n \overline{\mathcal{D}\mathcal{J}}(\psi^n)$$

(a_n, b_n) are chosen so that $\|\psi^{n+1}\|_{L^2(Y)} = 1$ and $\mathcal{J}(\psi^{n+1}) < \mathcal{J}(\psi^n)$

Two-directions optimization by projection algorithm (with phase ratio constraint $|Y_1| = |Y_2|$)



Maximizing horizontal and vertical and minimizing diagonal dispersions

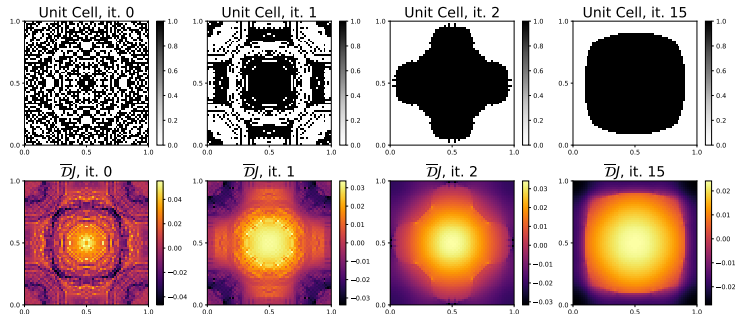
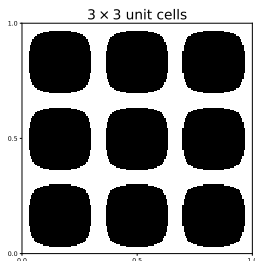
- Recall : $c(k, \mathbf{d}) = c_0(\mathbf{d}) + \frac{1}{2}(k\ell)^2 \frac{\gamma(\mathbf{d})}{c_0(\mathbf{d})} + o((k\ell)^2)$

- Cost functional:

$$J_{4d} = \frac{1}{2} \sum_{j=1}^2 \left(\frac{\gamma(\mathbf{d}_j)}{c_0(\mathbf{d}_j)} \right)^{-2} + \frac{1}{2} \sum_{j=3}^4 10 \left(\frac{\gamma(\mathbf{d}_j)}{c_0(\mathbf{d}_j)} \right)^2$$

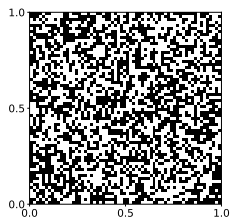
$$\mathbf{d}_j = (\cos \theta_j, \sin \theta_j), \quad \theta_{1,2} = 0, 90^\circ, \quad \theta_{3,4} = \pm 45^\circ$$

- Material ratios: $\mu_2/\mu_1 = 6$ and $\rho_2/\rho_1 = 1.5$

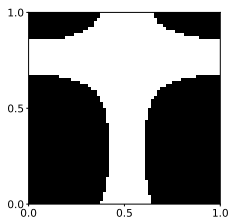


Other initializations with the same result

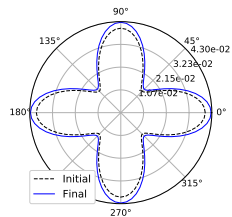
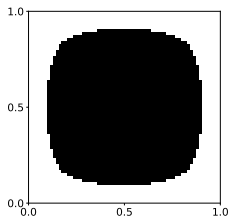
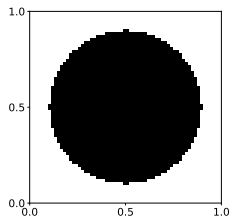
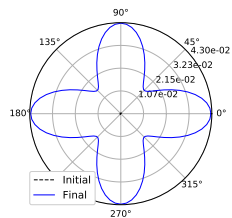
Initial cell



Final cell

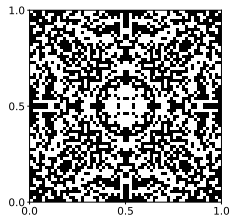


Dispersion indicator $\frac{\gamma(\mathbf{d})}{c_0(\mathbf{d})}$

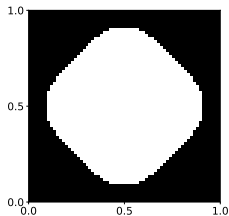


Initializations leading to sub-optimal results

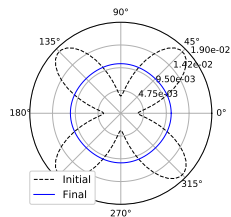
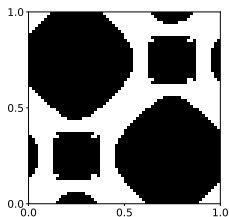
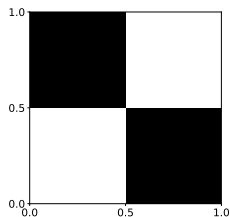
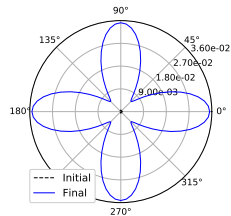
Initial cell



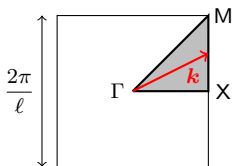
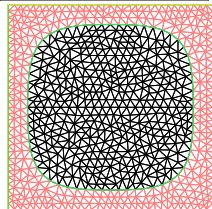
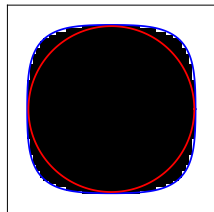
Final cell



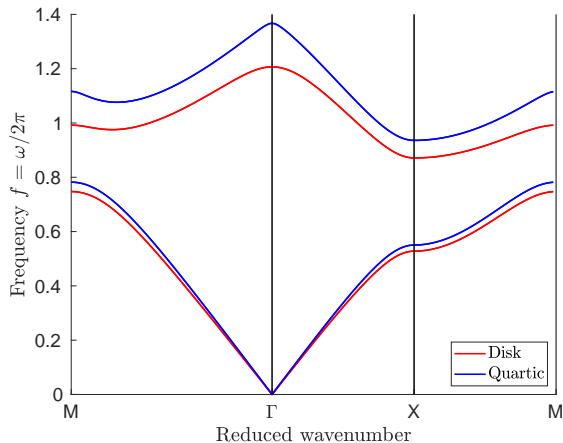
Dispersion indicator $\frac{\gamma(\mathbf{d})}{c_0(\mathbf{d})}$



Bloch-Floquet analysis of the optimal unit cell



- Fit of the optimal inclusion by a quartic curve.
- Finite element meshing using FREEFEM++ [Hecht, 2012, Laude, 2015]
- Computation of the first two Bloch frequencies in the reduced Brillouin zone.



Fitting an objective anisotropic phase velocity c^{obj}

- **Goal:** fitting phase velocity:

$$c^{\text{obj}}(k_p, \mathbf{d}_j) = c_0^{\text{obj}}(\mathbf{d}_j) + \Delta c^{\text{obj}}(k_p, \mathbf{d}_j), \quad p = 1..N_k, \quad j = 1..N_\theta$$

- Quasistatic and dispersive least-square cost functionals:

$$\mathcal{J}^{\text{stat}} = \frac{1}{2} \sum_{j=1}^{N_\theta} \left[c_0(\mathbf{d}_j) - c_0^{\text{obj}}(\mathbf{d}_j) \right]^2, \quad \mathcal{J}^{\text{dyn}} = \frac{1}{2} \sum_{j=1}^{N_\theta} \sum_{p=1}^{N_k} \left[\Delta c(k_p, \mathbf{d}_j) - \Delta c^{\text{obj}}(k_p, \mathbf{d}_j) \right]^2$$

- Weighted total cost functional:

$$\mathcal{J} = \alpha \mathcal{J}^{\text{stat}} + \mathcal{J}^{\text{dyn}}$$

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Example: chessboard reconstruction

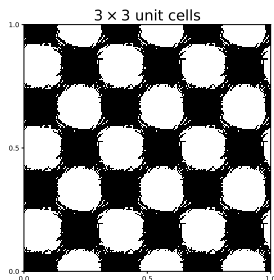
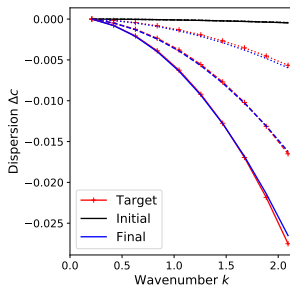
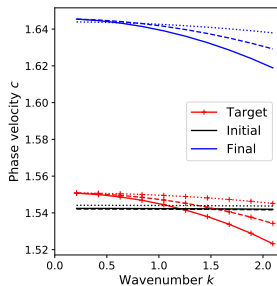
$\mu = 7$ $\rho = 1.2$	$\mu = 1$ $\rho = 1$
$\mu = 1$ $\rho = 1$	$\mu = 7$ $\rho = 1.2$

Data and constraints:

- $c^{\text{obj}} = c^{\text{chess}}$ (Floquet-Bloch, $N_\theta = 7$, $N_k = 10$)
- Exact material ratios
- Exact phase ratio $|Y_1| = |Y_2| = 1/2$

Chessboard reconstruction from phase velocity data

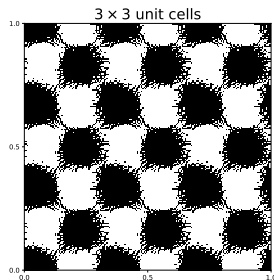
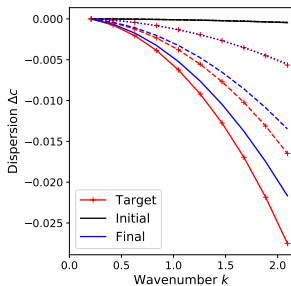
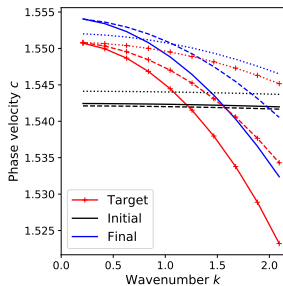
$$\alpha = 0 \quad (\mathcal{J} = \mathcal{J}^{\text{dyn}})$$



- : $\theta = -\pi/4$
- - - : $\theta = -\pi/8$
- ⋯ : $\theta = 0$

Chessboard reconstruction from phase velocity data

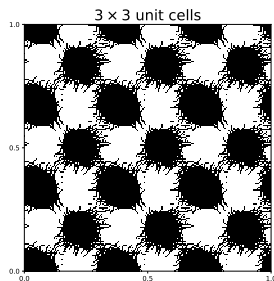
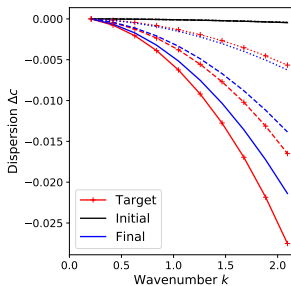
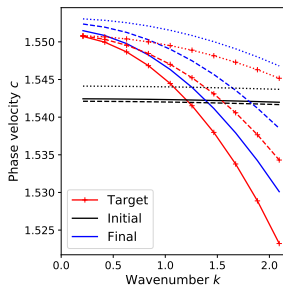
$$\alpha = 0.1$$



- : $\theta = -\pi/4$
- - - : $\theta = -\pi/8$
- ⋯ : $\theta = 0$

Chessboard reconstruction from phase velocity data

$$\alpha = 0.2$$



- : $\theta = -\pi/4$
- - - : $\theta = -\pi/8$
- · · : $\theta = 0$

Conclusions

- A topological optimization procedure is proposed, combining
 - ▶ A second-order dispersive homogenized model
 - ▶ The topological derivatives of this models's coefficients
 - ▶ A mixed algorithm combining level-set projection and pixel-by-pixel phase changes
 - ▶ FFT-based algorithm to solve cell problems
- The procedure is applied to various cost functionals to achieve
 - ▶ Maximization of dispersion in given directions
 - ▶ Qualitative identification of microstructures from effective behavior

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Perspectives

- Time-domain simulations of waves in the designed materials
- Extend the method to other geometrical and physical frameworks:
 1. **Periodic interfaces**: optimize *effective transmission conditions* [Marigo et al., 2017]
 2. **Elasticity**: links with *strain/stress gradient models* [Auffray et al., 2015].
 3. **High contrasts** [Pham et al., 2017] or **high frequencies** [Guzina et al., 2019] to optimize *band-gaps, memory effects* ...
- Improve the optimization algorithm
 - ▶ Compute a *pixel derivative* to work at a discrete level
 - ▶ Couple shape and topological derivative [Allaire et al., 2005, Amstutz et al., 2018]

Thanks for your attention !

Microstructural topological sensitivities of the second-order macroscopic model for waves in periodic media.
Marc Bonnet, Rémi Cornaggia, Bojan B. Guzina,
SIAM Journal on Applied Mathematics, 2018

Tuning effective dynamical properties of periodic media by FFT-accelerated topological optimization
Rémi Cornaggia, Cédric Bellis
International Journal for Numerical Methods in Engineering, 2020

<https://cv.archives-ouvertes.fr/remi-cornaggia>

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








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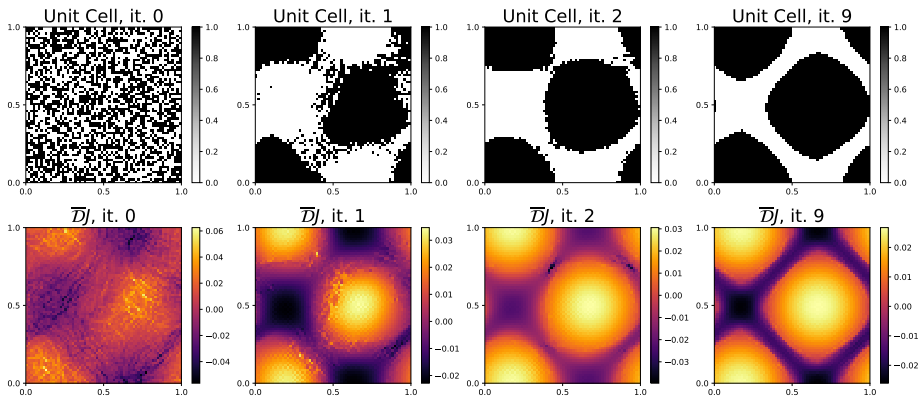


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Journal of the Mechanics and Physics of Solids, 78:382 – 414.

Minimizing horizontal and vertical and maximizing diagonal dispersions

- Cost functional: $J_{4d} = \frac{1}{2} \left(\lambda(\gamma_1^2 + \gamma_3^2) + \frac{1}{\gamma_2^2} + \frac{1}{\gamma_4^2} \right)$, $\theta_{1,3} = 0, 90^\circ$, $\theta_{2,4} = \pm 45^\circ$
- Material ratios: $\mu_2/\mu_1 = 6$ and $\rho_2/\rho_1 = 1.5$
- Stopping criterion: $\Theta < 10^{-3}$. Reached for $n = 9$: $\Theta_9 \approx 4.5 \times 10^{-8}$



Minimizing horizontal and vertical and maximizing diagonal dispersions

