

Effective Approximation for Elliptic PDEs with highly oscillating coefficients

Simon Ruget

Joint work with Claude Le Bris and Frédéric Legoll

École des Ponts ParisTech & Inria

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- 1 An inverse multiscale problem
- 2 Recovering an effective coefficient
- 3 Linearization through perturbative approaches

Inverse problem

Our study focuses on **inverse problems** for PDEs.

Consider an equation of the type

$$\mathcal{L}u = f.$$

- Is it possible to reconstruct the operator \mathcal{L} (namely its coefficients) from the knowledge of some solutions u ?
- Can other (coarser) observables be used to reconstruct \mathcal{L} ?

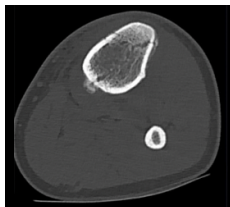


Figure 1: Bones echography showing two inclusions

Inverse multiscale problem

Our study focuses on inverse problems for **multiscale** PDEs :

$$\mathcal{L}_\varepsilon u_\varepsilon = f.$$

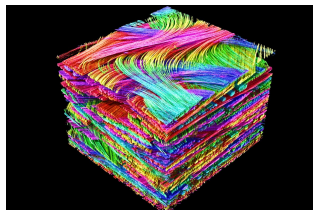


Figure 2: Composite material

Determining the fine-scale structure from measurements is an ill-posed problem... but identifying effective parameters is possible !

Inverse multiscale problem and ill-posedness

Consider the prototypical linear equation oscillating at the **small length scale** ε ,

$$\mathcal{L}_\varepsilon u_\varepsilon = -\operatorname{div}(A_\varepsilon \nabla u_\varepsilon) = f \text{ in } \Omega, \quad u_\varepsilon = 0 \text{ on } \partial\Omega, \quad (1)$$

with A_ε a bounded coercive coefficient.

Homogenization¹ assesses the existence of a limit equation when $\varepsilon \rightarrow 0$,

$$\mathcal{L}_\star u_\star = -\operatorname{div}(A_\star \nabla u_\star) = f \text{ in } \Omega, \quad u_\star = 0 \text{ on } \partial\Omega, \quad (2)$$

with A_\star an **effective** coefficient for which, in general, there exists no formula (abstract compactness result).

¹ see e.g. : A. Bensoussan, J.-L. Lions, G. Papanicolaou, *Asymptotic Analysis for Periodic Structures*, 1978.

Inverse multiscale problem and ill-posedness

Issue : in the limit $\varepsilon \rightarrow 0$, the observable u_ε is very close to u_\star whereas the operator we seek to reconstruct, \mathcal{L}_ε , is very different from \mathcal{L}_\star , its homogenized version.

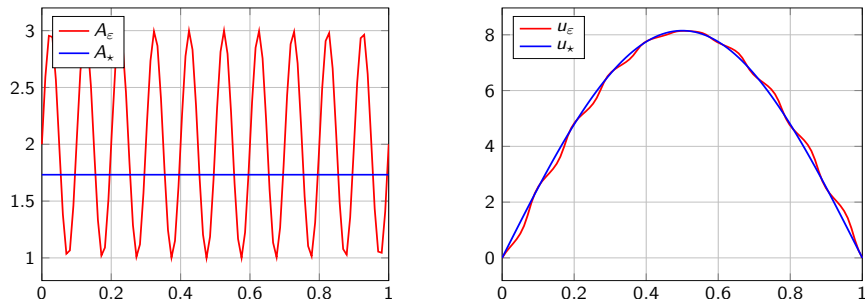


Figure 3: Two similar solutions associated to two distinct diffusion coefficients

Building an effective coefficient

Consider the multiscale diffusion problem (3)

$$\mathcal{L}_\varepsilon u_\varepsilon = -\operatorname{div}(A_\varepsilon \nabla u_\varepsilon) = f \text{ in } \Omega, \quad u_\varepsilon = 0 \text{ on } \partial\Omega. \quad (3)$$

From the knowledge of *observables* (to be explicitated latter) associated to solutions u_ε for various r.h.s. f , our aim is to propose a **numerical methodology** to build an **effective operator** $\overline{\mathcal{L}}$ approaching \mathcal{L}_ε .

Our strategy

- is inspired by homogenization theory,
- does not rely on classical hypothesis for homogenization (such as periodicity) which may be too restrictive in practical situations,
- is valid outside the regime of homogenization (i.e. $\varepsilon \rightarrow 0$),
- requires *few* prior information about the underlying system (the knowledge of $P \approx 3$ averaged observables is sufficient).

Previous work [CRAS2013]², [COCV2018]³

Idea : For $\bar{A} \in \mathbb{R}_{\text{sym}}^{d \times d}$ a *constant* symmetric coefficient, denote $\bar{u} = u(\bar{A}, f)$ the solution to

$$\bar{\mathcal{L}}\bar{u} = -\text{div}(\bar{A}\nabla\bar{u}) = f \text{ in } \Omega, \quad \bar{u} = 0 \text{ on } \partial\Omega. \quad (4)$$

The quality of the approximation of \mathcal{L}_ε by $\bar{\mathcal{L}}$ can be quantified through the functional

$$\sup_{\|f\|_{L^2(\Omega)}=1} \|u_\varepsilon(f) - u(\bar{A}, f)\|_{L^2(\Omega)}$$

Our strategy consists in **minimizing** the **worst case scenario** by looking at the optimization problem

$$\inf_{\bar{A} \in \mathbb{R}_{\text{sym}}^{d \times d}} \sup_{\|f\|_{L^2(\Omega)}=1} \|u_\varepsilon(f) - u(\bar{A}, f)\|_{L^2(\Omega)}$$

Issue : Using the **full solutions** u_ε **in the whole domain** Ω as observables is **disproportionate** to estimate a $d \times d$ constant symmetric matrix.

²C. Le Bris, F. Legoll, K. Li, CRAS, 2013.

³C. Le Bris, F. Legoll, S. Lemaire, ESAIM COCV, 2018.

Exploiting the energy

Coarser observables can be considered, such as the energy

$$\mathcal{E}(A_\varepsilon, f) = \frac{1}{2} \int_{\Omega} A_\varepsilon \nabla u_\varepsilon \cdot \nabla u_\varepsilon - \int_{\Omega} f u_\varepsilon. \quad (5)$$

Homogenization theory guarantees the convergence for energy :

$$\mathcal{E}(A_\varepsilon, f) \xrightarrow{\varepsilon \rightarrow 0} \mathcal{E}(A_\star, f) \text{ in } \mathbb{R}, \quad (6)$$

with

$$\mathcal{E}(A_\star, f) = \frac{1}{2} \int_{\Omega} A_\star \nabla u_\star \cdot \nabla u_\star - \int_{\Omega} f u_\star,$$

and where u_\star still denotes the solution to

$$\mathcal{L}_\star u_\star = -\operatorname{div}(A_\star \nabla u_\star) = f \quad \text{in } \Omega, \quad u_\star = 0 \quad \text{on } \partial\Omega.$$

Our strategy

For $\bar{A} \in \mathbb{R}_{\text{sym}}^{d \times d}$ a *constant* symmetric coefficient, denote $\bar{u} = u(\bar{A}, f)$ the solution to

$$\bar{\mathcal{L}}\bar{u} = -\text{div}(\bar{A}\nabla\bar{u}) = f \text{ in } \Omega, \quad \bar{u} = 0 \text{ on } \partial\Omega. \quad (7)$$

To assess the quality of the approximation of \mathcal{L}_ε by $\bar{\mathcal{L}}$, we use the functional

~~$$\sup_{\|f\|_{L^2(\Omega)}=1} \|u_\varepsilon(f) - u(\bar{A}, f)\|_{L^2(\Omega)} \longrightarrow \sup_{\|f\|_{L^2(\Omega)}=1} |\mathcal{E}(A_\varepsilon, f) - \mathcal{E}(\bar{A}, f)|$$~~

Our strategy consists in **minimizing** the **worst case scenario** by looking at the optimization problem

$$\inf_{\bar{A} \in \mathbb{R}_{\text{sym}}^{d \times d}} \sup_{\|f\|_{L^2(\Omega)}=1} |\mathcal{E}(A_\varepsilon, f) - \mathcal{E}(\bar{A}, f)|$$

In the limit of separated scales

In the limit of vanishing ε , the problem leads to the homogenized diffusion coefficient as shown by the following proposition.

$$I_\varepsilon = \inf_{\bar{A} \in \mathbb{R}_{\text{sym}}^{d \times d}} \sup_{\|f\|_{L^2(\Omega)}=1} |\mathcal{E}(A_\varepsilon, f) - \mathcal{E}(\bar{A}, f)|. \quad (8)$$

Proposition (Asymptotic consistency, periodic case)

For any sequence of quasi-minimizer $(\bar{A}_\varepsilon^\#)_{\varepsilon>0}$, i.e. sequence such that

$$I_\varepsilon \leq J_\varepsilon(\bar{A}_\varepsilon^\#) \leq I_\varepsilon + \varepsilon, \quad (9)$$

the following convergence holds :

$$\lim_{\varepsilon \rightarrow 0} \bar{A}_\varepsilon^\# = A_\star. \quad (10)$$

Proof for consistency proposition

$$\text{Let } J_\varepsilon(\bar{A}) = \sup_{\|f\|_{L^2(\Omega)}=1} |\mathcal{E}(A_\varepsilon, f) - \mathcal{E}(\bar{A}, f)|.$$

Lemma (Convergence for the energy)

In the periodic setting, we have

$$\lim_{\varepsilon \rightarrow 0} J_\varepsilon(A_\star) = 0.$$

We also use in the proof that the injection $H^1(\Omega) \subset L^2(\Omega)$ is compact.

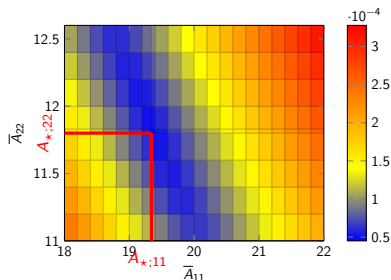


Figure 3: Isovalue of $J_\varepsilon(\bar{A})$.

Computational procedure

To solve

$$I_\varepsilon = \inf_{\bar{A} \in \mathbb{R}_{\text{sym}}^{d \times d}} \sup_{\|f\|_{L^2(\Omega)}=1} (\mathcal{E}(A_\varepsilon, f) - \mathcal{E}(\bar{A}, f))^2.$$

Given some iterate \bar{A}^n ,

- ① Define f^n , the argsup to

$$f \text{ s.t. } \|f\|_{L^2(\Omega)} = 1 \quad \left(\mathcal{E}(A_\varepsilon, f) - \mathcal{E}(\bar{A}^n, f) \right)^2.$$

In practice, $\sup_{f \in L^2(\Omega)} \rightarrow \sup_{f \in V_P}$ on $V_P = \text{Span}\{P \text{ r.h.s.}\}$, with $P \approx 3$.

This step requires computing P solutions to a coarse PDE in order to get the energy $\mathcal{E}(\bar{A}^n, \cdot)$. We next solve a $P \times P$ eigenvalue problem.

- ② Define \bar{A}^{n+1} , the optimizer to

$$\inf_{\bar{A} \in \mathbb{R}_{\text{sym}}^{d \times d}} (\mathcal{E}(A_\varepsilon, f^n) - \mathcal{E}(\bar{A}, f^n))^2.$$

In practice, we perform a gradient descent. The gradient can be expressed with solutions computed in step ①, hence no additional costs.

In practice, we perform $N \approx 10$ iterations of both steps.

Numerical results

We use an alternating direction algorithm in 2D ($\Omega = [0, 1]^2$) using the coefficient

$$A_\varepsilon(x, y) = A^{\text{per}}\left(\frac{x}{\varepsilon}, \frac{y}{\varepsilon}\right) = \begin{pmatrix} 22 + 10 \times (\sin(2\pi \frac{x}{\varepsilon}) + \sin(2\pi \frac{y}{\varepsilon})) & 0 \\ 0 & 12 + 2 \times (\sin(2\pi \frac{x}{\varepsilon}) + \sin(2\pi \frac{y}{\varepsilon})) \end{pmatrix}.$$

for which

$$A_\star \approx \begin{pmatrix} 19.3378 & 0 \\ 0 & 11.8312 \end{pmatrix}.$$

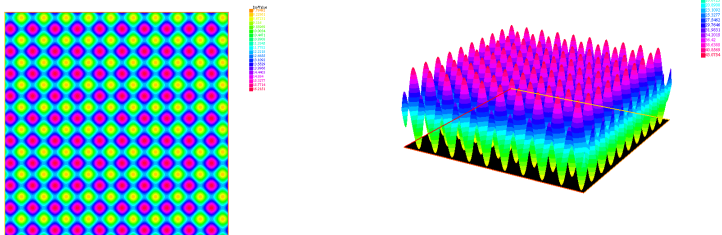


Figure 4: Components 11 and 22 of coefficient A_ε .

Consistency with homogenization theory

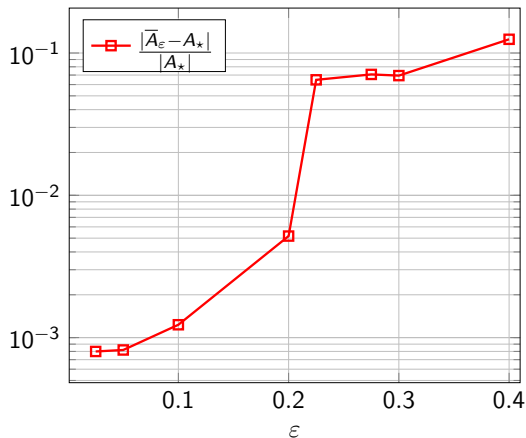


Figure 5: Error between the homogenized coefficient A_\star and the effective coefficient \bar{A}_ε as a function of ε .

Beyond the regime of separated scales

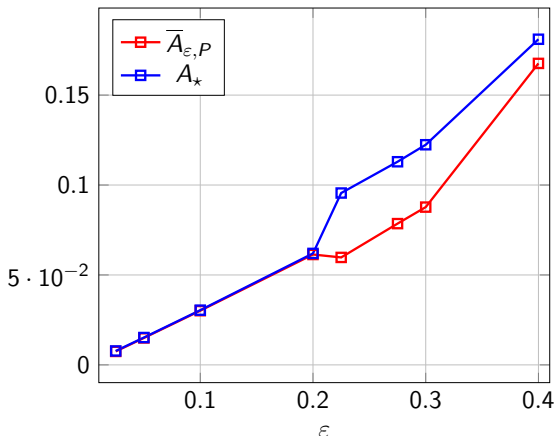


Figure 6: Error $\frac{\sup_{f \in V_Q} \|u_\varepsilon(f) - u(\bar{A}_{\varepsilon, P}, f)\|_{L^2(\Omega)}}{\|u_\varepsilon(\bar{f})\|_{L^2(\Omega)}}$ as a function of ε . (\bar{A}_ε is computed with $P \ll Q = 16$ r.h.s)

Beyond periodicity

We now use a non periodic coefficient (random checkerboard),

$$A_\varepsilon(x, y, \omega) = a^{\text{sto}} \left(\frac{x}{\varepsilon}, \frac{y}{\varepsilon}, \omega \right) = \left(\sum_{k \in \mathbb{Z}^2} X_k(\omega) \mathbb{1}_{k+Q}(x, y) \right) \text{Id},$$

with X_k i.i.d random variables such that $\mathbb{P}(X_k = 4) = \mathbb{P}(X_k = 16) = \frac{1}{2}$.

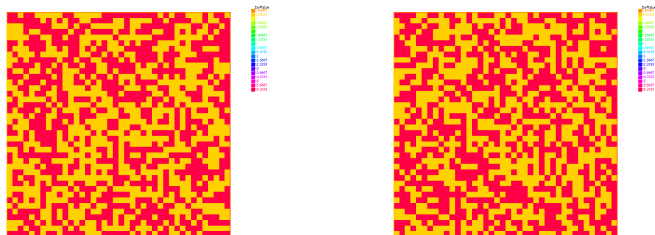


Figure 7: Two realizations of coefficient A_ε .

Our strategy rewrites $I_\varepsilon = \inf \sup |\mathbb{E}(\mathcal{E}(A_\varepsilon(\cdot, \omega), f)) - \mathcal{E}(\bar{A}, f)|$. Confidence intervals are computed from 40 realizations of the expectation (itself computed with a Monte Carlo method using 40 realizations of the coefficient a^{sto}).

Consistency with homogenization theory

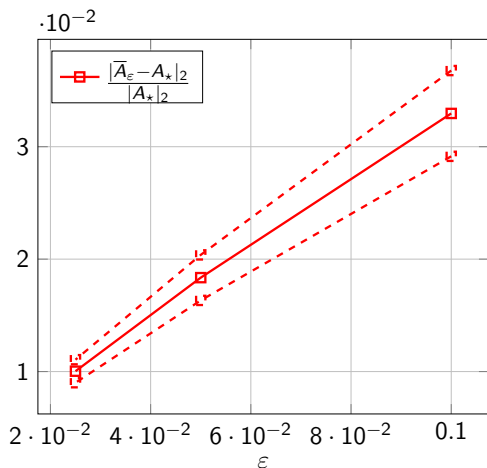


Figure 8: Error between the homogenized coefficient A_* and the effective coefficient \bar{A}_ε as a function of ε .

Beyond periodicity and the regime of separated scales

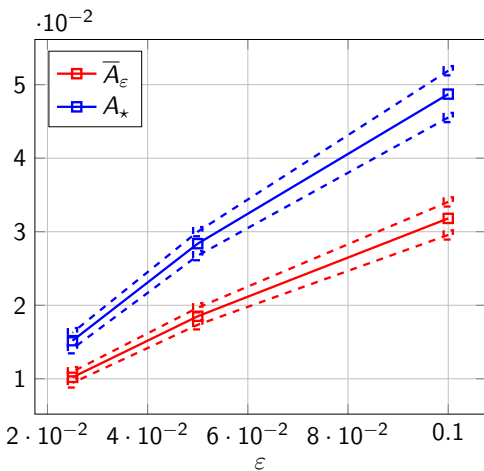


Figure 9: Error $\frac{\sup_{f \in V_Q} \|\mathbb{E}(u_\varepsilon(f, \omega)) - u(\bar{A}_\varepsilon, P, f)\|_{L^2(\Omega)}}{\|\mathbb{E}(u_\varepsilon(\bar{f}, \omega))\|_{L^2(\Omega)}}$ as a function of ε . (\bar{A}_ε is computed with $P \ll Q = 16$ r.h.s)

Perturbative approach

In some situations, we may initially know that A_ε is close to a [reference coefficient](#) A_ε^0 , and therefore that the coefficient A_\star we are looking for is close to a reference coefficient A_0 .

To take into account such information, we look for an effective coefficient in the form

$$\bar{A} = A_0 + \eta \bar{B} \quad (11)$$

and assume A_0 and η are known (η may represent the probability of defect in a material⁴).

For such \bar{A} , we have the [perturbative development](#)

$$\mathcal{E}(\bar{A}, f) \approx \mathcal{E}(A_0, f) + \eta \sum_{ij} \bar{B}_{ij} \int_{\Omega} f v_{ij}(A_0, f). \quad (12)$$

with v_{ij} depending only on A_0 and f .

⁴ see e.g. A. Anantharaman, C. Le Bris, MMS, 2011.

Linearization through a perturbative approach

The problem rewrites

$$\inf_{\bar{A}=A_0+\eta\bar{B}\in\mathbb{R}^{d\times d}} \sup_{\|f\|_{L^2(\Omega)}=1} \left(\mathcal{E}(A_\varepsilon, f) - \mathcal{E}(A_0, f) - \eta \sum_{ij} \bar{B}_{ij} \int_{\Omega} f v_{ij}(A_0, f) \right)^2$$

An advantage of this formulation is that the functional to optimize is **quadratic in \bar{B}** in contrast to the previous formulation.

This significantly **reduces the computational costs** provided the **offline** resolution of $P \times \frac{d(d+1)}{2}$ PDE to identify $v_{ij}(A_0, f_p)$.

Computational Procedure

Offline : Precompute $v_{ij}(A_0, f_p)$.

Online : Given an iterate $\bar{A}^n = A_0 + \eta \bar{B}^n$:

① Define f^n , the argsup to

$$\sup_{\|f\|_{L^2(\Omega)}=1} (\mathcal{E}(A_\varepsilon, f) - \mathcal{E}(A_0, f) - \eta \sum_{ij} \bar{B}_{ij} \int_{\Omega} f v_{ij}(A_0, f))^2$$

In practice, $\sup_{f \in L^2(\Omega)} \rightarrow \sup_{f \in V_P}$ with $P \approx 3$ r.h.s.

① Define $\bar{A}^{n+1} = A_0 + \eta \bar{B}^{n+1}$, the optimizer to

$$\inf_{\bar{A}=A_0+\eta\bar{B}} (\mathcal{E}(A_\varepsilon, f^n) - \mathcal{E}(A_0, f^n) - \eta \sum_{ij} \bar{B}_{ij} \int_{\Omega} f^n v_{ij}(A_0, f^n))^2$$

In practice, we perform a gradient descent. The gradient can be expressed with the quantity computed offline, hence no additional costs.

In practice, we need more iterations ($N_{\text{iter}} \approx 10^4$), but each iteration is essentially for free (no PDE to solve).

Numerical results

Let us consider a perturbed material

$$A_{\varepsilon,\eta}(x, y, \omega) = A_{\varepsilon}(x, y) + b_{\eta}(\omega)C_{\varepsilon}(x, y)$$

for which, in each cell of size ε , the probability of a defect from A_{ε} to $A_{\varepsilon} + C_{\varepsilon}$ is η .

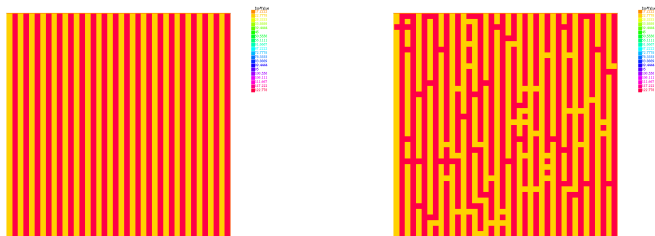


Figure 10: Coefficient $A_{\varepsilon,\eta}$ with $\eta = 0$ (left) and with $\eta = 0.1$ (right).

Recovering Effective Coefficient

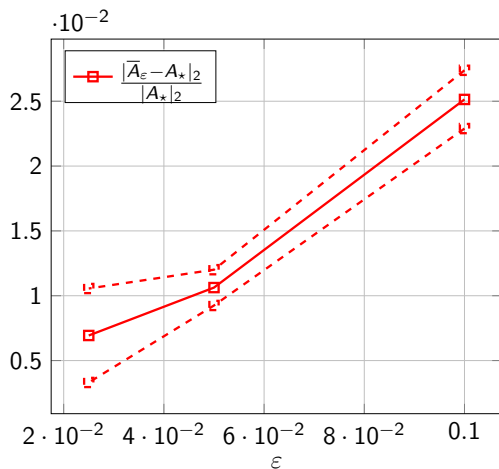


Figure 11: Error between the effective coefficient $\bar{A}_{\varepsilon,\eta}$ and the homogenized coefficient $A_{\star,\eta}$ ($\eta = 0.1$) as a function of ε .

Conclusion and ongoing works

Our strategy

- aims at **determining effective coefficients** for multiscale PDEs,
- is **inspired by homogenization theory** and **consistent with it** (numerically and theoretically),
- can be **extended outside the regime of separated scale**,
- requires **few prior information** on the system (coarse averages are sufficient),
- can be linearized in a **perturbative context** (hence reducing the computational cost).

Future works include **selection of effective coefficient** among a given list rather than identification.