A PARAMETER IDENTIFICATION PROBLEM IN STOCHASTIC HOMOGENIZATION

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William Minvielle An inverse problem in stochastic homogenization

Multiscale materials often leads to very expensive computations, and practical difficulties.

We consider a simple (linear) problem for a complex materials:

$$-\operatorname{div} \left[\begin{array}{cc} A_{\varepsilon}(x) \nabla u^{\varepsilon}(x) \right] = f(x) & x \in \mathcal{D} \subset \mathbb{R}^{d}, \\ u_{\varepsilon} = 0 & \partial \mathcal{D}. \end{array} \right]$$



Airplane wing.

Courtesy M. Thomas and EADS

$$-\mathrm{div} \ (A_{\boldsymbol{\varepsilon}}(x)\nabla u^{\boldsymbol{\varepsilon}}) = f \quad \mathrm{in} \quad \mathcal{D}, \qquad u^{\boldsymbol{\varepsilon}} = 0 \quad \mathrm{on} \quad \partial \mathcal{D}$$

	Application	A_{ε}	$u^{arepsilon}$	f
-				
1	Elasticity	elastic moduli	displacement	mechanical load
Therm	al conductivity	thermal conductivity	temperature	heat source
Ele	ectrostatics	permittivity	electric potential	charge density
Γ	Darcy flow	flow conductivity	pressure	sources

Multiscale materials Fruncation

Consider $A(y) \ge \mathbb{Z}^d$ -periodic matrix field.

$$-\operatorname{div}\left(A\left(\frac{x}{\varepsilon}\right)\nabla u^{\varepsilon}\right) = f \quad \text{in} \quad \mathcal{D}, \quad u^{\varepsilon} = 0 \quad \text{on} \quad \partial \mathcal{D} \tag{1}$$

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This difficult oscillatory problem homogenizes to:

$$-\operatorname{div} (A^* \nabla u^*) = f \quad \text{in} \quad \mathcal{D}, \quad u^* = 0 \quad \text{on} \quad \partial \mathcal{D}, \tag{2}$$

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The homogenized matrix A^* is defined by an average in the unit cell $Q = (0, 1)^d$ involving so-called correctors functions w:

$$A^{\star}e_j = \int_Q A(x) \left(\nabla w_{e_j}(x) + e_j\right) dx, \qquad (3)$$

and the (easy) corrector equation reads:

$$\begin{cases} -\operatorname{div} \left[A(\nabla w_p + p)\right] = 0 \quad \text{on } \mathbb{R}^d, \\ \nabla w_p \quad \text{periodic}, \ \int_Q \nabla w_p = 0. \end{cases}$$
(4)

An introduction to homogenization Setting

Multiscale materials Truncation



Courtesy M. Thomas and EADS

Multiscale materials Truncation

Consider $A(y, \omega)$ a stationary matrix field.

$$-\operatorname{div}\left(A\left(\frac{x}{\varepsilon},\omega\right)\nabla u^{\varepsilon}\right)=f\quad\text{in}\quad\mathcal{D},\qquad u^{\varepsilon}=0\quad\text{on}\quad\partial\mathcal{D}.$$

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where A^{\star} is defined by:

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ight] \, dy,$$

and the corrector equation, in \mathbb{R}^d , reads, for any $p \in \mathbb{R}^d$:

$$\begin{cases} -\text{div } [A(\nabla w_p + p)] = 0 \quad \text{in } \mathbb{R}^d \text{ a.s.}, \\ \nabla w_p \text{ stationary, } \int_Q \mathbb{E}[\nabla w_p] = 0. \end{cases}$$

Note that A^* (and hence u^*) is deterministic.

In practice, truncate over $Q_N := (0, N)^d$:

$$-\operatorname{div} \left[A(\nabla w_p^N + p)\right] = 0 \quad \text{in } Q_N \text{ a.s.}, \qquad w_p^N \quad Q_N - \text{periodic.}$$

$$A_N^{\star}(\omega)e_j := \frac{1}{|Q_N|} \int_{Q_N} A(y,\omega)(e_j + \nabla w_{e_j}^N(y,\omega)) dy.$$

For that reason alone, randomness comes again in the picture.

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In the sequel, we focus on computing $\mathbb{E}[A_N^*]$.

Introduce the estimator
$$\mathcal{I}_{M}^{MC} := \frac{1}{M} \sum_{m=1}^{M} A_{N}^{\star}(\omega_{m})$$
, where (ω_{m}) are i.i.d.

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Introduce the estimator $\mathcal{I}_{M}^{MC} := \frac{1}{M} \sum_{m=1}^{M} A_{N}^{\star}(\omega_{m})$, where (ω_{m}) are i.i.d.

$$A^{\star} - \mathcal{I}_{M}^{MC} = A^{\star} - \mathbb{E}[A_{N}^{\star}] + \mathbb{E}[A_{N}^{\star}] - \mathcal{I}_{M}^{MC}$$
(5)

The bias error is often small. The statistical error is *controlled by the variance*. Variance reduction approaches are useful to reduce the error.

$$\left|\mathbb{E}[A_N^{\star}] - \mathcal{I}_M^{MC}\right| \leq 1.96 \frac{\sqrt{\mathbb{V}\mathrm{ar}[A_N^{\star}]}}{\sqrt{M}}$$

F. Legoll and WM A control variate approach based on a defect-type theory for variance reduction in stochastic homogenization, 2014, Submitted. ArXiv 1407.8029

Physics Forward problem

An inverse problem in stochastic homogenization

joint work with

F. Legoll, A. Obliger, M. Simon.

F. Legoll, W.M., A. Obliger, M. Simon. A parameter identification problem in stochastic homogenization, 2014, arXiv 1402.0982. Accepted in ESAIM:ProcS.





Subsurface modeling (Courtesy PECSA, Paris VI)

Diffusion in clay modeled by the so-called Pore Network Model.



Physics Forward problem

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Diffusion in clay modeled by the so-called Pore Network Model.



Discrete elliptic equation $-\operatorname{div} \left[A(\frac{x}{\varepsilon}, \omega) \nabla u_{\varepsilon}\right] = f$

Can we recover some microscopic quantities

on the basis of

a few macroscopic quantities?

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Modelling:

- ▶ Diameters of channel: Weibull law $d_e \sim W(\lambda, k)$ i.i.d.
- Conductance: $A(x,\omega) = diag((d_{x,x+e_i}^4(\omega))_{j \in \{1,\dots,d\}}).$



Figure 1 : Weibull distributions.

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Forward problem: given $A(\cdot, \omega)$, compute

- Macroscopic permeability $A_N^{\star}(\omega)$.
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Inverse problem: given observed A_N^{\star} and $\mathbb{V}ar[A_N^{\star}]$, find λ, k .

An introduction to homogenization Setting

Physics Forward problem

Least square formulation



Figure 1 : For two choices of (λ, k) , convergence of $\mathbb{E}[A_N^{\star}]$ wrt $|Q_N|$ Continuous line: empirical mean. Dashed line: confidence intervals.

$$\left| \mathbb{E}[A_N^{\star}] - \mathcal{I}_M^{MC} \right| \le 1.96 \frac{\sqrt{\mathbb{Var}[A_N^{\star}]}}{\sqrt{M}}$$

A minimization problem

 A_{obs} : observed macroscopic *permeability*.

 V_{obs} : observed relative variance $\Rightarrow \operatorname{VarR}[X] := \operatorname{Var}[X]/\mathbb{E}[X]^2$

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Fix M realizations $\omega = (\omega_m)_{m \in \{1, \dots, M\}}$.

Problem: Find (λ, k) which minimizes F_M :

$$F_M(\lambda, \mathbf{k}; \omega) := \left(\frac{\mathcal{I}_M^{MC}(\omega)}{A_{obs}} - 1\right)^2 + \left(\frac{V_M^{MC}(\omega)}{V_{obs}} - 1\right)^2,$$

where
$$\mathcal{I}_{M}^{MC}(\omega) := \frac{1}{M} \sum_{m=1}^{M} A_{N}^{\star}(\omega_{m}), \ V_{M}^{MC}(\omega) := \mathbb{V}\mathrm{arR}^{M}[A_{N}^{\star}](\omega).$$

with $\mathbb{V}\mathrm{arR}^{M}[A_{N}^{\star}](\omega) := \frac{\frac{1}{M} \sum_{m=1}^{M} \left(A_{N}^{\star}(\omega_{m}) - \mathcal{I}_{M}^{MC}(\omega)\right)^{2}}{\mathcal{I}_{M}^{MC}(\omega)^{2}}$

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Newton algorithm (Derivatives of $F_M \Rightarrow \text{OK!}$)

1D

- Homogenization \Rightarrow OK!
- Minimization problem \Rightarrow Well posed!
- Numerics \Rightarrow Easy!

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- Numerics \Rightarrow Easy!

2D

- Homogenization \Rightarrow OK.
- Minimization problem \Rightarrow Theoretically unknown
- Numerics \Rightarrow More difficult

Landscape - Overview



Figure 2 : $F(\lambda, k)$ for $\lambda \in [1 \pm 50\%]$, $k \in [15 \pm 50\%]$.

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Landscape - Close-up



Figure 3 : $F(\lambda, k)$ for $\lambda \in [1 \pm 10\%]$, $k \in [15 \pm 10\%]$.

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Forward problem: statistical error



Random environment

- Compute a numerical target A_{obs} , V_{obs} with $\lambda = 1$, k = 15
- Run Newton
 - ▶ Starting from an initial guess 10% off,
 - Using a different environment.

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Figure 5 : Absolute error $(k^* = 15; \lambda^* = 1)$.

• Forward problem statistical error:

$$\mathbb{V}\mathrm{arR}\left[A_N^{\star}(\lambda^{\star},k^{\star})\right] \approx 1.4 \ 10^{-6} \qquad \mathbb{V}\mathrm{arR}\left[V_M^{MC}(\lambda^{\star},k^{\star})\right] \approx 10^{-3},$$

• Inverse problem error:

$$\mathbb{V}arR[\lambda_{opt}] \approx 7.9 \ 10^{-7} \quad \mathbb{V}arR[k_{opt}] \approx 1.7 \ 10^{-4}.$$

Accurate determination of the best λ , k.

2D Preliminary results



Figure 6 : Relative error $(k^* = 15; \lambda^* = 1)$.

2D Preliminary results



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With low values of N, M (N = 10, M = 30 !) we still get meaningful values of λ, k .

Conclusion

Future work: extension to the 2D case

- ► Homogenization with unbounded coefficients: without $c \le A(x, \omega) \le C \quad \forall x, \omega.$
- ▶ Numerical computations.

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Modeling issues

► Robustness of the best (λ, k) with respect to the observed values A_{obs}, V_{obs} ?

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Modeling issues

► Robustness of the best (λ, k) with respect to the observed values A_{obs}, V_{obs} ?

Numerical issues

▶ Tradeoff between N (RVE size) and M (# realizations)?