

An homogenization example of a material with non-conventional microstructure: thermal memory effect and uncertainties

<u>D. Dureisseix</u>, B. Faverjon, N. Blal (and participation of P. Royer – LMGC, R. Ameziane El Hassani – PFE)

> LaMCoS Univ Lyon, INSA Lyon, CNRS UMR 5259 27bis Avenue Jean Capelle 69 621 Villeurbanne, France



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Space-Time Multiscale Methods





Motivations

- Materials with microstructure Composites, on-demand tunable material (3D printed)...
 Mechanical engineering Thermo-mechanical behaviors Continuum mechanics models at both scales Microscale length ~ 0.01 mm – 1 cm
- Scale change: homogenization & relocalization



Outlines

- Kind of the scale transition approaches we use
- A specific example (not new: [Auriault 1983])
 Transient thermal behavior / high contrast phase A macroscopic memory effect
- Numerization of the homogenization (more recent: [DD et al 2015])
 Cell model, microscopic problem, macroscopic quantities
- Uncertainties in the micro-structure (on the way)
 Geometric parameters, non-intrusive approach



Spatial scales?

- Microstructure component: l
- Elementary representative volume: d
- Studied structure: L
- Separation? *l* < *d* << *L*

 $\varepsilon = d / L \text{ small}$









Reference problem: resolve the micro scale on the whole structure Often unaffordable...

 \Rightarrow "Decouple" the local resolution (at a micro/cell scale) from the global resolution (at the structure/macro/homogenized scale)

e.g. precompute on a single cell



Equivalence for the homogenized model



Which boundary conditions on the micro cell? Dirichlet, Neumann, self-consistent, periodic superposition... Different approaches, different results (bounds?)



(quasi-)Periodic homogenization

The elementary representative volume is an elementary (small) cell

1. A description with two spatial coordinates

Note that the spatial derivative is now $\frac{\partial}{\partial M} = \frac{\partial}{\partial x} + \frac{1}{\epsilon} \frac{\partial}{\partial y}$



2. Each field in your solution is asymptotically developed as: $U(x,y) = U_0(x,y) + \varepsilon U_1(x,y) + \varepsilon^2 U_2(x,y) + \dots$ each being *Y*-periodical



(quasi-)Periodic homogenization

3. Write the problem ODE, PDE... for any $\varepsilon \rightarrow 0$: identify the different powers of ε

One should obtain in the best case:

what the macro fields are

what the cell micro-problem is

what the homogenized macro problem is

and what the homogenized parameters are, how to relocalize the macro fields on the micro cell

Interesting features

- The approach embed the derivation of the homogenized model: used as a modeling tool
- Few parasitic boundary effects on the cell



Transient thermal (but linear) bi-phasic material with a large contrast in conductivity

Phases F and S

 $\begin{array}{l} \rho_F c_F \approx \rho_S c_S \\ k_F = \varepsilon^2 k'_F \text{ with } k'_F \approx k_S \end{array}$

Perfect interface between the phases Characteristic times

$$\tau_S = (\rho_S c_S / k_S) (l_S / \pi)^2$$

$$\tau_F = \frac{\rho_F c_F l_F^2}{k_F \pi^2} \approx \frac{\rho_F c_F L_F^2}{k_F' \pi^2} \approx \tau_S / \varepsilon^2 \approx \tau_M$$

 \Rightarrow A macro thermal load will lead to a micro answer visible at macro scale...



In practice...

Finite value of $\varepsilon = l / L$



ε = 1/10 : a big microstructure Does a *given* microstructure lead to a macroscopic memory effect? Depends on the structure size!

A macro memory effect arises only with contrast $O(\varepsilon^2)$



Lets do it...

- Asymptotic development of temperature fields $\theta = \sum \varepsilon^{\alpha} \theta_{\alpha}(x, y, t)$
- Develop the models (heat balance, bcs...)

- We obtain successively :
 - A macro S-temperature $\theta_{S0} = \theta_{S0}(x,t)$ $\underline{Z}_{S0}(x,t) = \underline{\operatorname{grad}}_x \theta_{S0}$
 - The micro problem for θ_{S_1} : a steady-state thermal problem, parametered with \underline{Z}_{So} as a load, on S-phase only leads to a relocalization operator for the micro-temperature gradient

$$\underline{Z}_{S1}(x, y, t) = -L_S(y)\underline{Z}_{S0}(x, t)$$

(note the linear dependency, L_s is computed once for all)



Lets do it...

We obtain successively:

- The problem giving θ_{F_0} : a transient thermal problem on the F-phase only, loaded with a boundary condition on the interface with $\theta_{S_{10}}$ but now $\theta_{F_0}(x, y, t)$ is not a macro-field only!
- A macro problem with a 2-field unknown...

$$C_{MS}\dot{\theta}_{S0} = \operatorname{div}_{x}(k_{MS}\underline{Z}_{S0}) - \left\langle \rho_{F}c_{F}\dot{\theta}_{F0} \right\rangle_{F}$$

with homogenized material parameters: capacity $C_{MS} = \langle \rho_S c_S \rangle_S$ conductivity $k_{MS} = \langle k_S (1 - L_S) \rangle_S$

And we stop here the asymptotic development...



Lets do it...

Interpretation:

$$C_{MS}\dot{\theta}_{S0} = \operatorname{div}_{x}(k_{MS}\underline{Z}_{S0}) - \left\langle \rho_{F}c_{F}\dot{\theta}_{F0} \right\rangle_{F}$$

At this scale, θ_{Fo} can be seen as a field of internal variables, serving as memorizing the past evolution of the material

But, defined at the micro scale, it is too huge to store at every time step

 \Rightarrow An equivalent (hereditary) model with a memory function

$$C_{MS}\dot{\theta}_{S0} = \operatorname{div}_x(k_{MS}\underline{Z}_{S0}) + \int_{\tau=-\infty}^{\tau=t} \ddot{\theta}_{S0}(\tau)\beta(t-\tau)d\tau$$



Lets do it...

Interpretation:

$$C_{MS}\dot{\theta}_{S0} = \operatorname{div}_x(k_{MS}\underline{Z}_{S0}) + \int_{\tau=-\infty}^{\tau=\iota} \ddot{\theta}_{S0}(\tau)\beta(t-\tau)d\tau$$

 $\beta(t)$ is also a macroscopic material characteristic (back-in-time function)

Semi-analytical solution (1D stratified composite):

$$\beta(t) \approx \rho_F c_F n \frac{8}{\pi^2} \exp[-t/\tau_F]$$

evanescent memory with a characteristic time τ_F a.k.a. kernel, resolvent, Duhamel integral... see also Prony series...



Numerization

For a 3D microstructure... rely on simulation

Pre-compute on a cell to provide

Capacity C_M : simple average (analytical)

Conductivity \mathbf{k}_{M} : requires to solve few (3) steady-state thermal micro-problems, and provides also the relocalization operator \mathbf{L}_{S} to rebuilt the micro-solution as post-treatment once the homogenized problem is solved

Memory effect function $\beta(t)$: requires to solve a transient thermal micro-problem

(every micro-problem is linear here, hence easy to pre-compute once for all, with periodic boundary conditions and macro loading)







Limitations

As for any approach: edge effects

Close to structure boundary: periodicity assumption does not hold any more...



 \Rightarrow Higher order corrections or local reanalysis (DDM, MGM, zoom...)



Limitations

Non-linear behavior issue

Linear \Rightarrow superposition, easy pre-computation

Non-linear \Rightarrow less easy...





Limitations

Non-linear behavior issue

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Non-linear \Rightarrow less easy...

Try to avoid identical or similar solves (and store computed knowledge)





Motivation

On-demand material tuning:

Goal-oriented design of the microstructure

Target performance of the macroscopic behavior

First step:

manufacturing process uncertainties \Rightarrow influence on the macroscopic behavior

Issues

- Multiple parameters
- Multiple queries

Carnot Ingénierie@Lyon project: MURMUR (Multiscale robust design of material microstructures), LaMCoS project: MaDAMe_R² (Multiscale Design of Advanced Materials using Rapid and Robust approaches))



Issues

- Multiple parameters
- Multiple queries
- What is needed (which quantity of interest?, full cdf, first moments, level of confidence, envelops...)

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Black-box MCS (Monte-Carlo Simulations)	QMS ROM Collocation-PCE (Quasi Monte-Carlo, Surrogate models)	Stochastic FE code / PCE (Polynomial chaos expansion)

Cost (?) – depends on the number of parameters...



Non-intrusive collocation-based PCE



- No matter if linear or non-linear (black-box)
- Computational complexity 1 with the number of parameters
- If QoI = macro characteristics (C_M, \mathbf{k}_M, β),

 \Rightarrow How do uncertainties propagate through scales?



Non-intrusive collocation-based PCE



Representation of a random variable X :

from a basic r.v. set ξ ψ_i = orthogonal polynomial basis

 X_i = coefficient

$$X(\boldsymbol{\xi}) = \sum_{i=0}^{p} X_{i} \psi_{i}(\boldsymbol{\xi})$$

Input: given a stochastic distribution \Rightarrow particular polynomial basis QoI: identify the coefficients by projection/least square on a set of runs (collocation points for inputs)



- Uncertain input parameters:
 - Phase material characteristics
 - Geometry parametrization



distortion (stochastic distribution: uniform)

elongation (stochastic distribution: uniform)



Uncertain Qol:

example of macroscopic conductivity \mathbf{k}_{M} eigenvalues coefficients of variation:

inputs			Qol	
micro conductivity <i>k_F</i>	distortion	elongation	$k_{MI} = k_{MII}$	k _{mili}
0	0	1	0	0
0.3536	0		0.0845	0.0919
0	2.582		0.0907	0.0921
0.3536	2.582		0.1718	0.181



Outlooks and prospects

- Robust design of ad hoc microstructures
- Optimization (many query problem also)
 - Performance ⇒ QoI = macro characteristics
 - Integrity ⇒ QoI = relocalization operator/field (tensor representation/decomposition...)
- Topological optimization at both scales
- Increasing the number of parameters (curse of dimensionality)



Some references

- Auriault, Effective macroscopic description for heat conduction in periodic composites, International Journal of Heat and Mass Transfer, 1983. <u>doi:10.1016/S0017-9310(83)80110-0</u>
- Dureisseix et al. Numerization of a memory effect for a homogenized composite material with a large contrast in the phase thermal conductivities, International Journal of Heat and Mass Transfer, 2015. <u>hal-01171181</u>, <u>doi:10.1016/j.ijheatmasstransfer.2015.06.048</u>
- Sanchez-Palencia, Non homogeneous media and vibration theory, 1980. doi:10.1007/3-540-10000-8
- Feyel and Chaboche, Multi-scale non-linear FE2 analysis of composite structures: damage and fiber size effects, Revue Européenne des Éléments Finis, 2001. <u>doi:10.1080/12506559.2001.11869262</u>
- Fishman, Monte Carlo: concepts, algorithms, and applications. Springer series in operations research, 1995. doi:10.1007/978-1-4757-2553-7
- Ghanem and Spanos, Stochastic Finite Elements: A Spectral Approach, 1991. doi:10.1007/978-1-4612-3094-6
- Eldred, Recent advances in non-intrusive polynomial chaos and stochastic collocation methods for uncertainty analysis and design, 2009. <u>doi:10.2514/6.2009-2274</u>
- Oladyshkin and Nowak, Data-driven uncertainty quantification using the arbitrary polynomial chaos expansion, Reliability Engineering & System Safety, 2012. <u>doi:10.1016/j.ress.2012.05.002</u>