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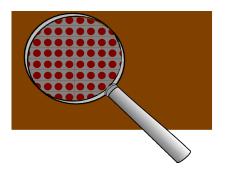
A problem of optimal design of composites

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Oct. 25th, 2007

Composite materials



Composites are engineered materials made from two or more constituent materials with significantly different physical properties (For ex. Thermal conductivity). The mixing of the materials is at a small scale, we compute the conductivity properties at a larger scale by a process called homogenization.

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Periodic composites

In a periodic two-component composite, the conductivity at each point is given by a periodic function a with the following form in the unit cube Q.

$$a(x) = egin{cases} \sigma_1 & ext{if } x \in A \ \sigma_2 & ext{if } x \in Q \setminus A \end{cases}$$

$$a(x) = \sigma_1$$

Where A is the part of the cube covered by the first constituent material.

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homogenization

If the function ${\it a}$ is periodic in cubes of size $\varepsilon,$ we have equations like

$$\operatorname{div}(a(x/\varepsilon)\nabla u^{\varepsilon}(x)) = f(x)$$

As $\varepsilon \to 0$, the solutions u^{ε} will converge to a solution u to the *homogenized* problem:

$$\operatorname{div}(A_{\operatorname{eff}}\nabla u(x)) = f(x)$$

where the matrix $A_{\rm eff}$ depends on σ_1 , σ_2 and the exact shape of the set A.

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Cell problem

Formula to obtain $A_{\rm eff}$

The matrix A_{eff} is a self-adjoint matrix such that

$$\langle A_{\mathsf{eff}} v, v \rangle = \min_{w \in H^1_{\mathsf{per}}(Q)} \int_Q a(x) |v + \nabla w|^2 \, \mathrm{d}x.$$

Note that $\langle A_{\text{eff}} v, v \rangle$ is the energy of a function $u(x) = x \cdot v + w(x)$ that is periodic perturbation of a plane and solves

$$\operatorname{div}(a(x)\nabla u) = 0 \quad \text{in } Q$$

Interpretation of the cell problem



The function $u = x \cdot v + w$ is a periodic perturbation of a plane that solves $div(a(x)\nabla u) = 0$ in Q.

$$\langle A_{\mathsf{eff}} \; v, v \rangle = \min_{w \in H^1_{\mathsf{per}}(Q)} \int_Q \mathsf{a}(x) |v + \nabla w|^2 \; \mathrm{d}x.$$

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Shape optimization

Interpretation of the cell problem



In a coarser scale, the function u approximates a plane. Its energy is still $\langle A_{\text{eff}}v, v \rangle$.

$$\langle A_{\mathsf{eff}} | v, v \rangle = \min_{w \in H^1_{\mathsf{per}}(Q)} \int_Q \mathsf{a}(x) |v + \nabla w|^2 \, \mathrm{d}x.$$

Shape optimization

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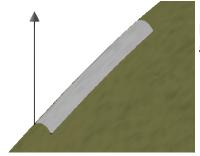


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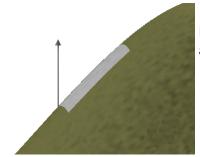


In an even larger scale, it could be a piece of a smooth function.

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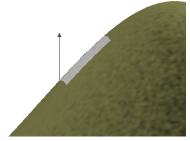


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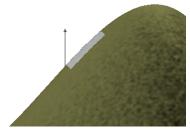


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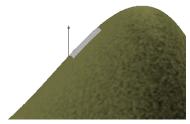


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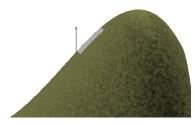


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Effective conductivity.

In general A_{eff} is a selfadjoint $n \times n$ matrix.

In case the set A (the part of the unit cube occupied by the first component) is cubically symmetric, then we know A_{eff} will be a scalar $a_{\text{eff}}I$.

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First Question of optimization.

Question

Given $\sigma_1 < \sigma_2$ and $\mu > 0$, what is the maximum value that a_{eff} can take for all cubically symmetric shapes A such that $|A| = \mu$?

Answer

The maximum conductivity is given by the Hashin-Shtrikman bound:

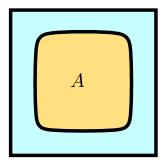
$$a_{\mathsf{eff}} \leq \mu \sigma_1 + (1-\mu) \sigma_2 - rac{\mu (1-\mu) (\sigma_2 - \sigma_1)^2}{(n \sigma_2 + (1-\mu) (\sigma_1 - \sigma_2))}$$

Moreover, there is a unique connected shape A that realizes the bound and it is given by the contact set of an obstacle problem.

General Vigdergauz structures

The unique connected shape A that achieves the Hashin-Shtrikman bound is the contact set of the following *obstacle* problem.

- q is a Q-periodic function.
- $q \geq -|x|^2$ in Q.
- riangle q(x) = k for every x where $q(x) > -|x|^2$.
- $riangle q(x) \leq k$ in Q.



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A more symmetric problem

Consider a composite where one constituent is a good thermal conductor (conductivity 1) but a bad electric conductor (conductivity ε). The other has the exact oposite properties: thermal conductivity ε and electric conductivity 1.

Let $a_{\rm eff}$ and $b_{\rm eff}$ be the effective thermal and electric conductivities of the mix.

In a series of papers, Torquato, Hyun and Donev studied the problem of maximizing $a_{\rm eff} + b_{\rm eff}$ from all cubically symmetric shapes A in 3D such that |A| = |Q|/2. Not that if we exchange A with $Q \setminus A$, the quantity $a_{\rm eff} + b_{\rm eff}$ does not change.

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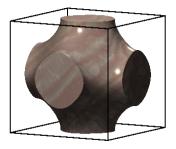
Bergman's bounds

Using classical cross-property bounds due to Bergman (1978), we can obtain the following upper bound in 3D:

$$a_{ ext{eff}} + b_{ ext{eff}} \leq (1 + arepsilon) - rac{(1 - arepsilon)^2}{3(1 + arepsilon)}.$$

Question: Is the bound achievable?

Pseudo-answer: Numeric computations by Torquato, Hyun and Donev suggest it is.

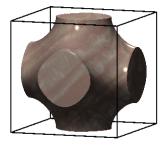


The expected shape of an optimal structure *A* would be triply connected.

Moreover $Q \setminus A$ would be triply connected too.

Moreover A and $Q \setminus A$ should be congruent sets due to the symmetry of the problem.

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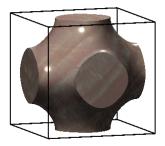
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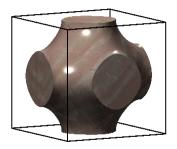
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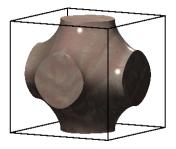
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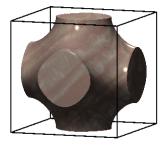
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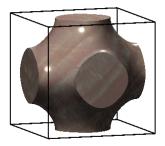
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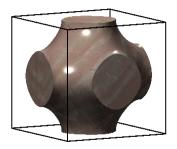
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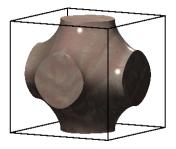
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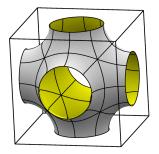
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Conjecture.

From the numeric computations it was natural to believe that ∂A was the Schwartz *P* surface.

The Schwartz P surface is a bicontinuous periodical minimal surface.



Picture of the Schwartz *P* surface from the website of Ken Brakke.

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Characterization of optimal structures

Theorem

Bergman's upper bound is achieved for a set $A \subset Q$ if and only if the periodic solution to

$$riangle q = \left\{egin{array}{ccc} 1 & \mbox{in } A \ -1 & \mbox{in } Q \setminus A \end{array}
ight.$$

satisfies

$$D^{2}q(x) = \begin{cases} M(x) + \nu \otimes \nu & \text{on the A side of } \partial A \\ M(x) - \nu \otimes \nu & \text{on the } Q \setminus A \text{ side of } \partial A \end{cases}$$

for some matrix M such that $M(x) \cdot \nu = 0$.

Proof in the blackboard.

Counterproof of the conjecture

Question

Can Bergman's upper bound be achieved if ∂A has mean curvature zero?

If that was the case, it can be shown that

- q is constant (= 0) on ∂A .
- q_{ν} is also constant on ∂A .

So, at the same time we would have that q^+ and q^- solve the one phase problem, and q solves the two-phase membrane problem.

For a given set A, these conditions can be checked numerically in a very simple way. Indeed, they are **not** satisfied if ∂A is the Schwartz P surface.