

Strong and weak error estimates for the solutions of elliptic partial differential equations with random coefficients

Julia Charrier
ENS Cachan Bretagne/ INRIA Rennes

24 november 2010
Journée d'équipe d'analyse numérique

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$$\operatorname{div}(a(x)\nabla p(x)) = 0 \quad \forall x \in D \subset \mathbb{R}^d$$

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- the **homogeneous lognormal** model: $a(\omega, x) = e^{g(\omega, x)}$,
 where g is a mean-free **gaussian field**, its law is uniquely determined
 by the covariance function supposed to be homogeneous, i.e.

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- Goal: **compute the law of $p : \Omega \rightarrow H^1(D)$** i.e. the $\mathbb{E}[\varphi(p)](x)$
 in practice, we compute the first two moments, i.e. the functions
 $\mathbb{E}[p](x)$ and $\mathbb{E}[p^2](x)$.

Equation and assumptions

- D a bounded open C^2 domain of \mathbb{R}^d , (Ω, \mathcal{F}, P) a probability space
- $a : \Omega \times \bar{D} \rightarrow \mathbb{R}$ a **lognormal homogeneous** random field
 $a(\omega, x) = e^{g(\omega, x)}$ where g is a gaussian homogeneous mean-free random field with $\text{cov}[g](x, y) = k(\|x - y\|)$, $k \in C^{0,1}(\mathbb{R})$
- We look for $u : \Omega \times D \rightarrow \mathbb{R}$ such that for almost every ω

$$\begin{cases} -\text{div}(a(\omega, \cdot) \nabla u(\omega, \cdot)) & = f(x) & \text{on } D \\ u(\omega, \cdot) & = 0 & \text{on } \partial D. \end{cases}$$

Proposition

For almost all ω , $a(\omega, \cdot) \in \mathcal{C}^{0,\alpha}(\bar{D})$ for any $\alpha < \frac{1}{2}$.

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Key point of the proof:

Theorem (Kolmogorov)

Let $X(\omega, x) : \Omega \times D \subset \mathbb{R}^d \rightarrow \mathbb{R}^n$ be a stochastic process such that there exists a constants C , $p > 1$ and $\varepsilon > 0$ such that for any $x, y \in D$ we have

$$\mathbb{E}[\|X(\omega, x) - X(\omega, y)\|^p] \leq C\|x - y\|^{d+\varepsilon},$$

then for almost all ω , $X(\omega, \cdot) \in \mathcal{C}^{0,\beta}(\bar{D})$ for any $\beta < \frac{\varepsilon}{p}$.

Proposition

We can then define for almost all ω :

$$a_{\min}(\omega) = \min_{x \in \bar{D}} a(\omega, x) \text{ and } a_{\max}(\omega) = \max_{x \in \bar{D}} a(\omega, x).$$

Then $\frac{1}{a_{\min}(\omega)} \in L^p(\Omega)$ and $a_{\max}(\omega) \in L^p(\Omega) \forall p > 0$.

Key point of the proof:

Theorem (Fernique)

If E is a separable Banach space and X a mean-free gaussian random variable with values in E , then there exists $\alpha > 0$ such that

$$\mathbb{E}[e^{\alpha \|X\|_E^2}] < \infty,$$

in particular, for any $p > 0$, we have $\mathbb{E}[e^{p \|X\|_E}] < \infty$.

Proposition

The equation

$$\begin{cases} -\operatorname{div}(a(\omega, \cdot) \nabla u(\omega, \cdot)) & = f(x) & \text{on } D \\ u(\omega, \cdot) & = 0 & \text{on } \partial D. \end{cases}$$

admits a unique solution $u \in L^p(\Omega, H_0^1(D)), \forall p > 0$.

Proof

For a.e. ω , the equation admits a unique solution $u(\omega, \cdot) \in H_0^1(D)$ with

$$\|u(\omega, \cdot)\|_{H_0^1(D)} \leq \frac{C_D}{a_{\min}(\omega)} \|f\|_{L^2(D)}.$$

Therefore

$$\|u\|_{L^p(\Omega, H_0^1(D))} \leq C_D \|f\|_{L^2(D)} \left\| \frac{1}{a_{\min}} \right\|_{L^p(\Omega)}.$$

Approximation of a

We approximate the random field $a(\omega, x)$ by a function of x and of N random variables, i.e. in a finite dimensional stochastic space:

$$a(\omega, x) \rightsquigarrow \tilde{a}(Y_1(\omega), \dots, Y_N(\omega), x).$$

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- It is the first and fundamental step of several numerical methods: some perturbation-type methods, and mostly the **spectral stochastic methods**: stochastic collocation methods and stochastic galerkin methods.

Basic introduction to the stochastic collocation method

- By Doob Dynkin lemma, the solution u of the equation: for a.e. ω

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can be expressed as a function of $Y(\omega) = (Y_1(\omega), \dots, Y_N(\omega))$ and x ,
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- The equation solved by \bar{u} is then: for any $y = (y_1, \dots, y_N) \in \mathbb{R}^N$

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- If Y admits the density $\rho: \mathbb{R}^N \rightarrow \mathbb{R}$, then $\mathbb{E}[\varphi(\tilde{u}(\omega, x))] = \int_{\mathbb{R}^N} \varphi(\bar{u}(y, x)) \rho(y) dy \in H^1(D)$ can be approximated with quadrature rules in \mathbb{R}^N , i.e. by $\sum_{i=1}^{P_N} \lambda_i \varphi(\bar{u}(y_i, x))$.
 \rightsquigarrow the computational cost increases drastically with N .

Approximation of a

How to approximate a ?

- Let $(\lambda_n, b_n)_{n \in \mathbb{N}}$ be the eigenpairs of the Hilbert-Schmidt operator:

$$f \in L^2(D) \longmapsto \left(x \mapsto \int_D \text{cov}[g](x, y) f(y) dy \right) \in L^2(D)$$

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We define, for $n \in \mathbb{N}$, $Y_n(\omega) = \frac{1}{\sqrt{\lambda_n}} \int_D g(\omega, x) b_n(x) dx$.

The $(b_n)_n$ and the $(Y_n)_n$ are **orthonormal**.

The $(Y_n)_{n \geq 1}$ are **independent** because g is gaussian.

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- Then the **Karhunen-Loève expansion** of g is:

$$g(\omega, x) \stackrel{L^2(\Omega \times D)}{=} \sum_{n=1}^{+\infty} \sqrt{\lambda_n} b_n(x) Y_n(\omega)$$

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- We approximate then g by the truncated expansion at order N ,
 $g_N(\omega, x) = \sum_{n=1}^N \sqrt{\lambda_n} b_n(x) Y_n(\omega)$.

- We define the approximation a_N of a :

$$a_N(\omega, x) = e^{g_N(\omega, x)} = e^{\sum_{n=1}^N \sqrt{\lambda_n} b_n(x) Y_n(\omega)}.$$

- We define the **approximation a_N** of a :

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- We define the **approximation u_N** of u as the solution of:

$$\begin{aligned} -\nabla \cdot (a_N(\omega, \cdot) \nabla u_N(\omega, \cdot)) &= f(x) \text{ on } D \\ u_N(\omega, \cdot) &= 0 \text{ on } \partial D. \end{aligned}$$

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- Our aim is to **estimate the error** committed by **approximating** u by u_N .

Strong convergence of a_N to a

Assumptions:

- the eigenfunctions b_n are continuously differentiable with $\|b_n\|_\infty \leq C$ and $\|\nabla b_n\|_\infty \leq Cn^a$ for some $a \geq 0$,
- $\sum_{n \geq 1} \lambda_n n^b < +\infty$ for some $b > 0$.

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Strong convergence of g_N to g

- **Kolmogorov theorem** yields:
 $\forall p > 0, \forall 0 < \alpha < \min\{b, 2a\}$

$$\|g_N - g\|_{L^p(\Omega, C^0(\bar{D}))} \leq A_{\alpha,p} \sqrt{\sum_{n>N} \lambda_n n^\alpha} \quad \forall N \in \mathbb{N}.$$

- **Borel-Cantelli lemma** yields:
for almost all ω , $g_N \xrightarrow{C^0(\bar{D})} g$ and so $a_N \xrightarrow{C^0(\bar{D})} a$ as $N \rightarrow +\infty$.

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for almost all ω , $g_N \xrightarrow{C^0(\bar{D})} g$ and so $a_N \xrightarrow{C^0(\bar{D})} a$ as $N \rightarrow +\infty$.
- We define $a_N^{\min}(\omega) = \min_{x \in \bar{D}} a_N(\omega, x)$ and $a_N^{\max}(\omega) = \max_{x \in \bar{D}} a_N(\omega, x)$ a.s.
Then **Fernique theorem** yields that for all $p > 0$,

$$\left\| \frac{1}{a_N^{\min}} \right\|_{L^p(\Omega)} \leq B_p \text{ and } \|a_N^{\max}\|_{L^p(\Omega)} \leq B_p \quad \forall N \in \mathbb{N}.$$

Strong convergence of u_N to u

$\forall p > 0, \forall 0 < \alpha < \min\{b, 2a\}$

$$\|a_N - a\|_{L^p(\Omega, C^0(\bar{D}))} \leq C_{\alpha, p} \sqrt{\sum_{n>N} \lambda_n n^\alpha} \quad \forall N \in \mathbb{N}.$$

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Theorem

$\forall p > 0, \forall 0 < \alpha < \min\{b, 2a\}$

$$\|u_N - u\|_{L^p(\Omega, H_0^1(D))} \leq F_{\alpha,p} \sqrt{\sum_{n>N} \lambda_n n^\alpha} \quad \forall N \in \mathbb{N}.$$

Weak convergence of u_N to u

Theorem

There exists a constant C such that for any $\varphi \in C^4(\mathbb{R}, \mathbb{R})$ whose derivatives are bounded by a constant C_φ

$$\|\mathbb{E}_\omega[\varphi(u) - \varphi(u_N)]\|_{H_0^1} \leq C_\varphi \sum_{n>N} \lambda_n.$$

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Remark: The weak order is twice the strong order.

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Remark: The weak order is twice the strong order.

Sketch of the proof: We recall that: $u_N(\omega, x) = u_N(Y_1(\omega), \dots, Y_N(\omega), x)$. For any N , for any multi-index $\alpha \in \mathbb{N}^N$, and any $y \in \mathbb{R}^N$, we have

$$\left\| \frac{\partial^\alpha u_N(y, x)}{\partial y^\alpha} \right\|_{H_0^1(D)} \leq k_{|\alpha|} \sqrt{\frac{a_N^{\max}(y)}{a_N^{\min}(y)}} \|u_N(y)\|_{H_0^1} C^{|\alpha|} \prod_{i \in \mathbb{N}} \sqrt{\lambda_i^{\alpha_i}},$$

where $k_{|\alpha|}$ is a constant independent of N and depending only on the length of α .

Formally, in the particular case of the expected value, we have:

$$\begin{aligned} & u(\omega, x) - u_N(\omega, x) \\ &= u(Y_1(\omega), \dots, Y_N(\omega), Y_{N+1}(\omega), \dots, x) - u(Y_1(\omega), \dots, Y_N(\omega), 0, \dots, x) \end{aligned}$$

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The independence of the Y_i yields:

$$\mathbb{E}[u - u_N](x) = 0 + \frac{1}{2} \sum_{i>N} \mathbb{E} \left[\frac{\partial^2 u}{\partial y_i^2}(Y_1(\omega), \dots, Y_N(\omega), 0, \dots, x) \right] + \dots$$

Example: the 1D exponential covariance case

We take $D = (0, 1)$ and $\text{cov}[g](x, y) = \sigma^2 e^{-\frac{|x-y|}{l}}$ where l is the correlation length. Then we have analytic expressions for the eigenvalues λ_n and the eigenfunctions b_n , in particular :

- $\lambda_n \underset{n \rightarrow +\infty}{\sim} \frac{2\sigma^2}{l\pi^2 n^2}$
- $\forall n \in \mathbb{N}, \|b_n\|_\infty \leq C$ and $\|b'_n\|_\infty \leq Cn$.

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Proposition (Strong convergence result)

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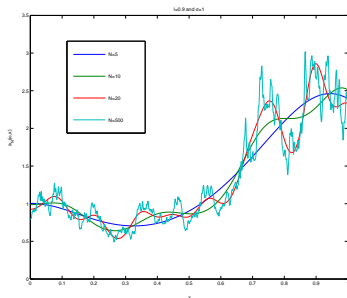
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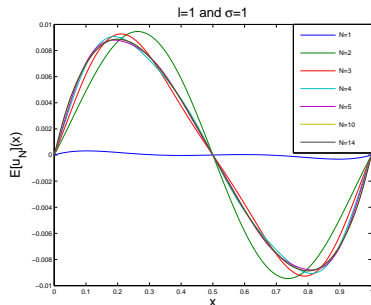
Proposition (Weak convergence result)

For any $\varphi \in C^4(\mathbb{R}, \mathbb{R})$ whose derivatives are bounded by a constant C_φ

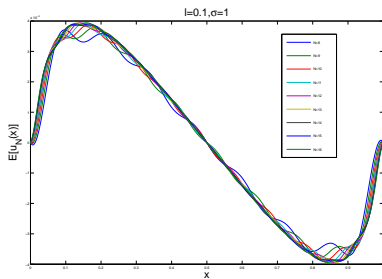
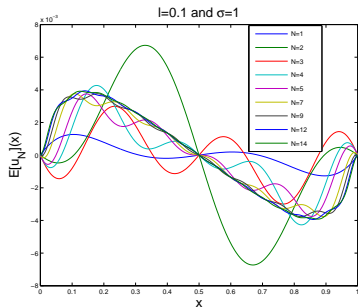
$$\|\mathbb{E}_\omega[\varphi(u) - \varphi(u_N)]\|_{H_0^1(D)} \leq \frac{C_\varphi}{N}.$$



$u_N(\omega, x)$ for different values of N



$\mathbb{E}[u_N(x)]$ for different values of N
 here we have $\|E[u - u_N]\|_{L^2(D)} \simeq \frac{c}{N^{2.7}}$.



$\mathbb{E}[u_N(x)]$ for different values of N , in the case where $l = 0.1$, $\sigma = 1$.

Example: the 2D exponential covariance case

We take $D = (0, 1)^2$ and $\text{cov}[g](x, y) = \sigma^2 e^{-\frac{\|x-y\|_1}{l}}$ where l is the correlation length.

The set of the eigenpairs (λ_n, b_n) is obtained as the tensor product of the 1D eigenpairs.

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Proposition (Strong convergence result)

$\forall p > 0, \forall 0 < \alpha < 1$

$$\|u_N - u\|_{L^p(\Omega, H_0^1(D))} \leq F_{\alpha, p} N^{\frac{\alpha-1}{2}} \quad \forall N \in \mathbb{N}.$$

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Proposition (Weak convergence result)

For any $\varphi \in C^4(\mathbb{R}, \mathbb{R})$ whose derivatives are bounded by a constant C_φ , for any $\varepsilon > 0$, we get

$$\|\mathbb{E}_\omega[\varphi(u) - \varphi(u_N)]\|_{H_0^1(D)} \leq \frac{C_{\varphi, \varepsilon}}{N^{1-\varepsilon}}.$$

Example: the analytic covariance case

We suppose that $\text{cov}[g]$ is analytic on D^2 , then we have

Theorem (Schwab, Todor)

- $$\lambda_n \leq c_1 e^{-c_2 n^{1/d}} \quad \forall n \in \mathbb{N}$$
- for any $s > 0$ there exists a constant c_s such that,

$$\|b_n\|_\infty \leq c_s |\lambda_n|^{-s} \text{ and } \|b'_n\|_\infty \leq c_s |\lambda_n|^{-s} \quad \forall n \in \mathbb{N}.$$

We have then strong and weak convergence results, analogous to the previous results.

Proposition (Strong convergence result)

For any $0 < s < \frac{1}{2}$, and $p > 0$

$$\|u - u_N\|_{L^p(\Omega, H_0^1(D))} \leq H_{s,p} \sqrt{\sum_{n>N} \lambda_n^{1-2s}} \quad \forall N \in \mathbb{N}$$

therefore

$$\|u - u_N\|_{L^p(\Omega, H_0^1(D))} \leq l_{d,s,p} N^{\frac{d-1}{2d}} e^{-\frac{c_2(1-2s)}{2} N^{1/d}} \quad \forall N \in \mathbb{N}$$

Proposition (Weak convergence result)

For any $0 < s < \frac{1}{2}$, for all $\varphi \in C^4(\mathbb{R}, \mathbb{R})$ whose derivatives are bounded by a constant C_φ , we have:

$$\|\mathbb{E}[\varphi(u_N) - \varphi(u)]\|_{H_0^1(D)} \leq J_s C_\varphi \sum_{n>N} \lambda_n^{1-2s} \quad \forall N \in \mathbb{N}$$

therefore

$$\|\mathbb{E}[\varphi(u_N) - \varphi(u)]\|_{H_0^1(D)} \leq K_{d,s} C_\varphi N^{\frac{d-1}{d}} e^{-c_2(1-2s)N^{1/d}} \quad \forall N \in \mathbb{N}.$$

- Let u_N^h be the approximation of u_N in a standard linear finite element space with a regular triangulation \mathcal{T}_h .
- For any $y \in \mathbb{R}^N$, $u_N(y) \in H^2(D)$ with

$$\|u_N(y)\|_{H^2(D)} \leq C \frac{\|f\|_{L^2(D)}}{a_N^{\min}(y)} \left(1 + \frac{a_N^{\max}(y)}{a_N^{\min}(y)}\right) \left(1 + \frac{a_N^{\max}(y)}{a_N^{\min}(y)} + \frac{\|a'_N(y)\|_{L^\infty(D)}}{a_N^{\min}(y)}\right).$$

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- Therefore, thanks to Céa lemma and the usual approximation result, we get

$$\|u_N(y) - u_N^h(y)\|_{H_0^1(D)} \leq C \sqrt{\frac{a_N^{\max}(y)}{a_N^{\min}(y)}} \frac{\|f\|_{L^2(D)}}{a_N^{\min}(y)} \left(1 + \frac{a_N^{\max}(y)}{a_N^{\min}(y)}\right) \left(1 + \frac{a_N^{\max}(y)}{a_N^{\min}(y)} + \frac{\|a'_N(y)\|_{L^\infty(D)}}{a_N^{\min}(y)}\right) h.$$

Proposition

For any $p > 0$, we have

$$\|u_N - u_N^h\|_{L^p(\Omega, H_0^1(D))} \leq C_{N,p} h.$$

If moreover the eigenfunctions $b_n \in C^2$ and there exists $0 < \theta < 1$ such that

$$\sum_{n \geq 1} \lambda_n \|Db_n\|_{\infty}^{2(1-\theta)} \|D^2 b_n\|_{\infty}^{2\theta} < \infty,$$

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Proposition (J.C,R.Scheichl,A.Teckentrup)

For any $0 < s < 1/2$, $p > 0$, we have

$$\|u_N - u_N^h\|_{L^p(\Omega, H_0^1(D))} \leq C_{s,p} h^s.$$