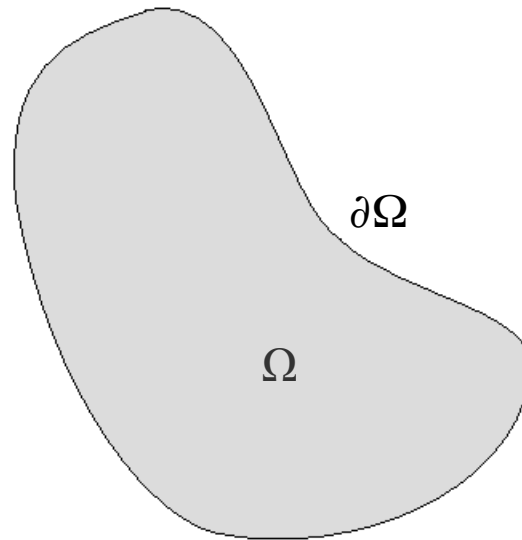


Deterministic boundary value problem

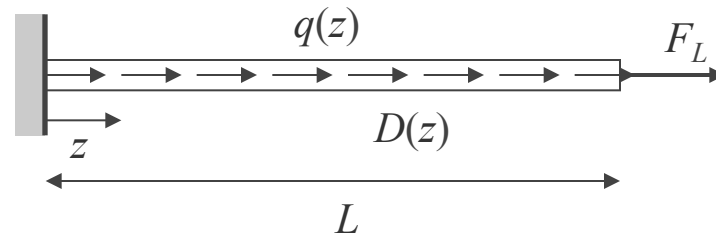
General boundary value problem



$$\begin{aligned} & \mathbf{L}(\mathbf{z}) \cdot \mathbf{u}(\mathbf{z}) + \mathbf{f}(\mathbf{z}) = 0 \quad \text{in } \Omega \\ \text{given } & \mathbf{u}(\mathbf{z})|_{\Gamma_0} = 0, \nabla \mathbf{u}(\mathbf{z})|_{\Gamma_1} = \bar{\mathbf{t}} \quad \Gamma_0 \cup \Gamma_1 = \partial\Omega \end{aligned}$$

Deterministic boundary value problem

Static equilibrium of a bar



$$\frac{d}{dz} \left(D(z) \frac{du(z)}{dz} \right) + q(z) = 0 \quad \text{in } [0, L]$$

$$\text{given } u(0) = 0, \frac{du}{dz} \Big|_L = \frac{F_L}{D(L)}$$

Stochastic boundary value problem

General boundary value problem

$$\begin{aligned} & \mathbf{L}(\mathbf{z}, \theta) \cdot \mathbf{u}(\mathbf{z}, \theta) + \mathbf{f}(\mathbf{z}, \theta) = 0 \quad \text{in } \Omega \\ \text{given} \quad & \mathbf{u}(\mathbf{z}, \theta)|_{\Gamma_0} = 0, \nabla \mathbf{u}(\mathbf{z}, \theta)|_{\Gamma_1} = \bar{\mathbf{t}} \quad \Gamma_0 \cup \Gamma_1 = \partial\Omega \end{aligned}$$

Static equilibrium of a bar

$$\begin{aligned} & \frac{d}{dz} \left(D(z, \theta) \frac{du(z, \theta)}{dz} \right) + q(z, \theta) = 0 \quad \text{in } [0, L] \\ \text{given} \quad & u(0, \theta) = 0, \frac{du}{dz} \Big|_L = \frac{F_L(\theta)}{D(L, \theta)} \end{aligned}$$

Stochastic boundary value problem

Static equilibrium of a bar

$$\frac{d}{dz} \left(D(z, \theta) \frac{du(z, \theta)}{dz} \right) + q(z, \theta) = 0 \quad \text{in } [0, L]$$

given $u(0, \theta) = 0, \frac{du}{dz} \Big|_L = \frac{F_L(\theta)}{D(L, \theta)}$

- Choose a complete functional space Θ
- Define a subspace Θ_n of Θ spanned by a finite set of functions $\{N_i(z), i = 1, \dots, n\}$
- Approximate $u(z, \theta)$ as

$$u_h(z, \theta) = \sum_{i=1}^n u_i(\theta) N_i(z)$$

Galerkin method

Residual:
$$R(u_h(z, \theta), z) = \frac{d}{dz} \left(D(z, \theta) \frac{du_h(z, \theta)}{dz} \right) + q(z, \theta)$$

Inner product of the residual with any test function $v(z) \in \Theta_n$ that satisfies $v(0) = 0$ vanishes

$$\Rightarrow \int_0^L v(z) R(u_h(z, \theta), z) dz = 0$$

$$\Rightarrow \dots \Rightarrow \int_0^L \frac{dv(z)}{dz} D(z, \theta) \frac{du_h(z, \theta)}{dz} dz = \int_0^L v(z) q(z, \theta) dz + v(L) F_L(\theta)$$

Set:

$$u_h(z, \theta) = \sum_{i=1}^n u_i(\theta) N_i(z) \qquad v(z) = \sum_{i=1}^n v_i N_i(z)$$

...

Galerkin method

...

$$\mathbf{K}(\theta)\mathbf{u}(\theta) = \mathbf{F}(\theta)$$

where:

Stochastic stiffness matrix:

$$K_{ij}(\theta) = \int_0^L \frac{dN_i(z)}{dz} D(z, \theta) \frac{dN_j(z)}{dz} dz$$

Stochastic force vector:

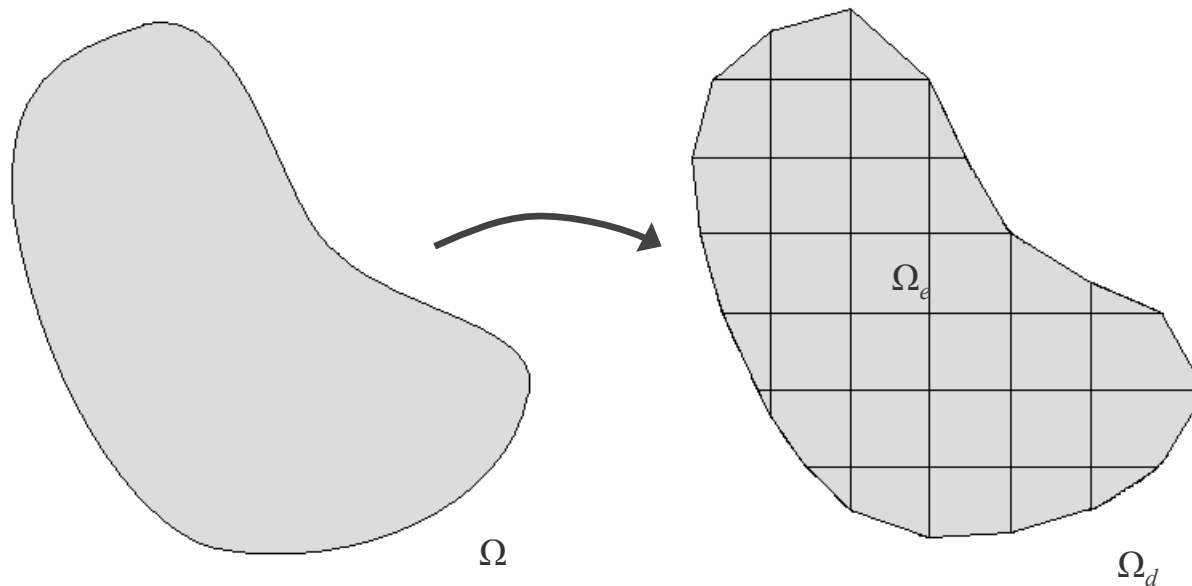
$$F_i(\theta) = \int_0^L N_i(z) q(z, \theta) dz + N_i(L) F_L(\theta)$$

Stochastic vector of random unknowns:

$$\mathbf{u}(\theta) = [u_1(\theta); u_2(\theta); \dots; u_n(\theta)]$$

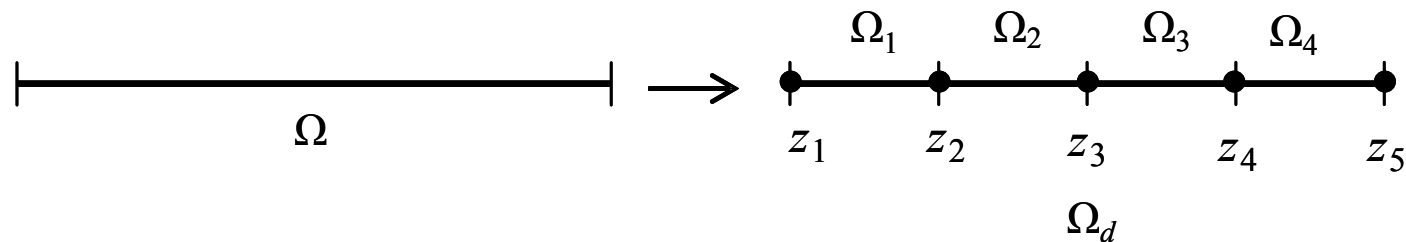
Finite element shape functions

Discretize the domain with a finite number of polygonal elements

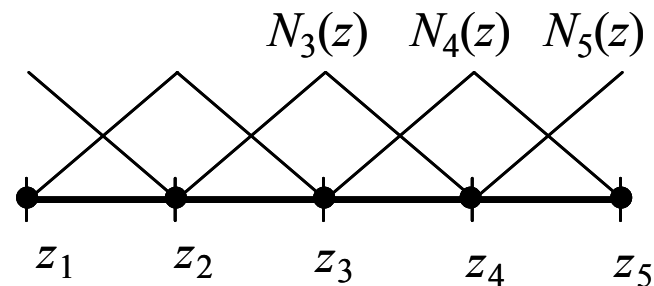


Finite element shape functions

Discretize the domain with a finite number of polygonal elements



Choose the basis functions as piece-wise linear polynomials that interpolate linearly between the nodes



Properties of finite element shape functions

- The i th shape function equals one at node i and zero at all other nodes

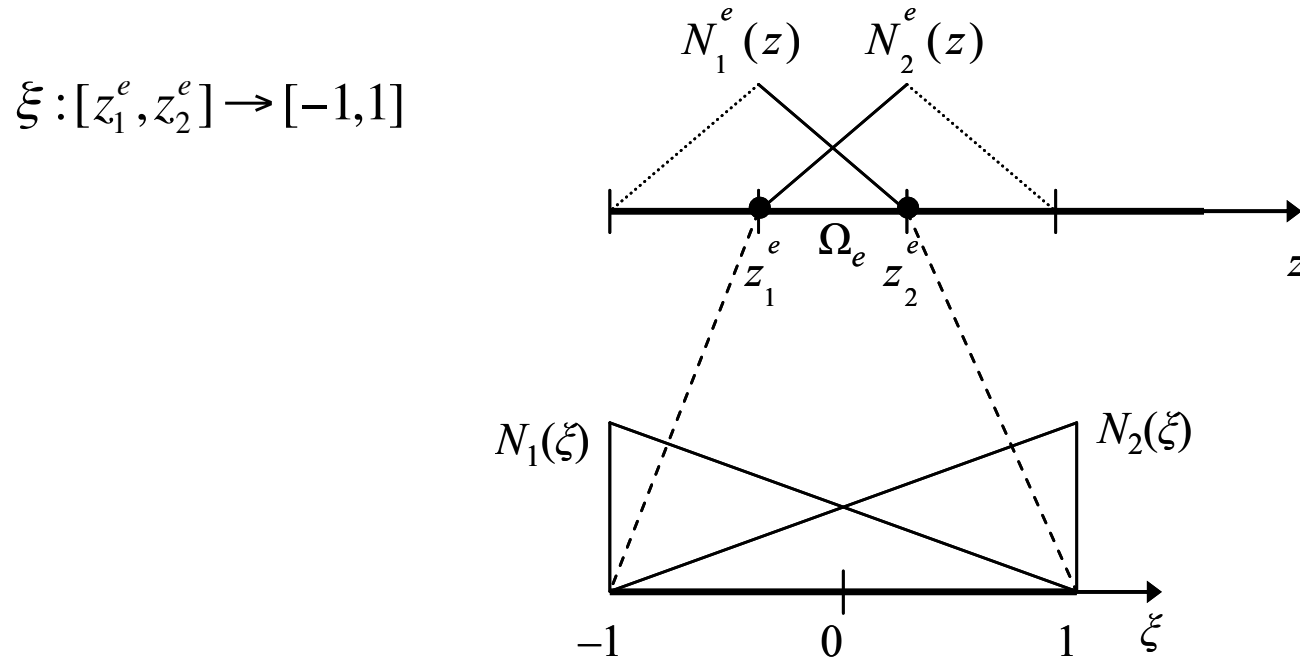
$$N_i(z) = \begin{cases} 1 & \text{for } z = z_i \\ 0 & \text{for } z = z_j, j \neq i \end{cases}$$

- Partition of unity

$$\sum_{i=1}^n N_i(z) = 1$$

Local (element) shape functions

- Define a linear mapping to a standard elemental domain:



- Local shape functions

$$N_1(\xi) = \frac{1}{2}(1 - \xi) \quad N_2(\xi) = \frac{1}{2}(1 + \xi)$$

Element stiffness matrix and force vector

$$\mathbf{K}(\theta) = \sum_{e=1}^{n_e} \mathbf{K}^e(\theta)$$

$$\mathbf{F}(\theta) = \sum_{e=1}^{n_e} \mathbf{F}^e(\theta)$$

Element stochastic stiffness matrix:

$$\mathbf{K}^e(\theta) = \frac{1}{2h^e} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \int_{-1}^1 D(z, \theta) d\xi$$

Element stochastic force vector:

$$\mathbf{F}^e(\theta) = \frac{h^e}{2} \int_{-1}^1 q(z, \theta) \begin{bmatrix} \frac{1-\xi}{2} \\ \frac{1+\xi}{2} \end{bmatrix} d\xi$$

Note: If e is the last element

$$F_2^e(\theta) = \frac{h^e}{2} \int_{-1}^1 N_2(\xi) q(z, \theta) d\xi + F_L(\theta)$$

Discretization of random fields

Approximation of $D(z, \theta)$ and $q(z, \theta)$ with a finite number of random variables

$$D(z, \theta) \approx D(z, \mathbf{X}) \quad q(z, \theta) \approx q(z, \mathbf{X})$$

Mean-square and variance discretization errors:

$$err_{\text{m-s}}(z) = \mathbb{E} \left[\left(D(z, \theta) - D(z, \mathbf{X}) \right)^2 \right] \quad err_{\text{Var}}(z) = \text{Var} \left[D(z, \theta) - D(z, \mathbf{X}) \right]$$

Global discretization errors:

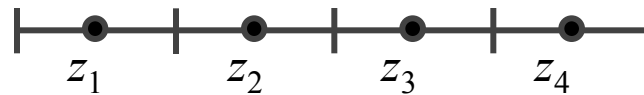
$$\overline{err}_{\text{m-s}} = \frac{1}{L} \int_0^L err_{\text{m-s}}(z) dz$$

$$err_{\text{m-s}} = \sup_{z \in \Omega} err_{\text{m-s}}(z)$$

Point discretization methods

- Choose a number of points in the domain
- Approximate the random field in terms of the random variables corresponding to these points

Midpoint method



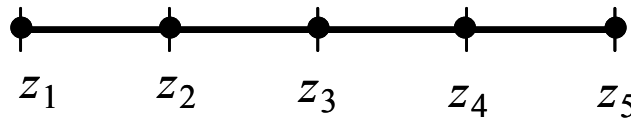
Random variables in the discretization: $X_i = D(z_i, \theta)$

Random field approximation: $D(z, \mathbf{X}) = X_i \quad \text{for } z \in \Omega_i$

Point discretization methods

- Choose a number of points in the domain
- Approximate the random field in terms of the random variables corresponding to these points

Shape function method



Random variables in the discretization: $X_i = D(z_i, \theta)$

Random field approximation:
$$D(z, \mathbf{X}) = \sum_{i=1}^n X_i N_i(z)$$

Note: The random field representing the displacements $u(z, \theta)$ is discretized by the shape function method

Point discretization methods

Example

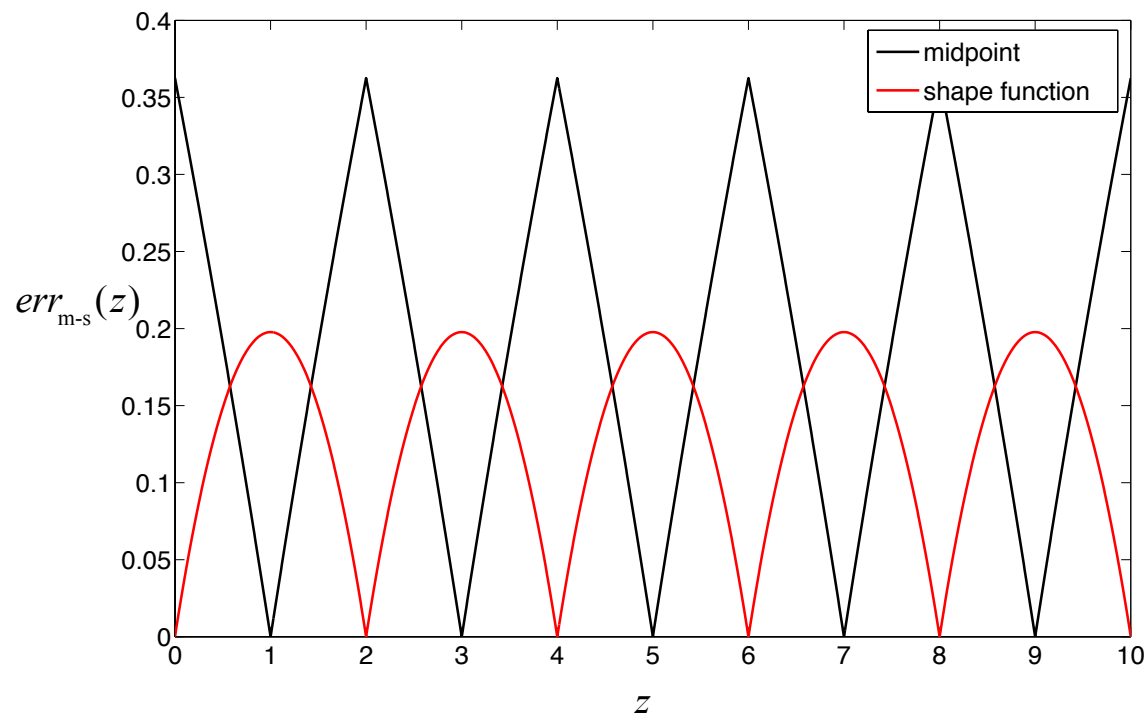
- 1D homogeneous Gaussian random field in $[0, 10]$
- Autocorrelation coefficient function: $\rho(\xi) = \exp\left(-\frac{2|\xi|}{\theta}\right)$

Point discretization methods

Example

Comparison of midpoint and shape function methods

Local point-wise error

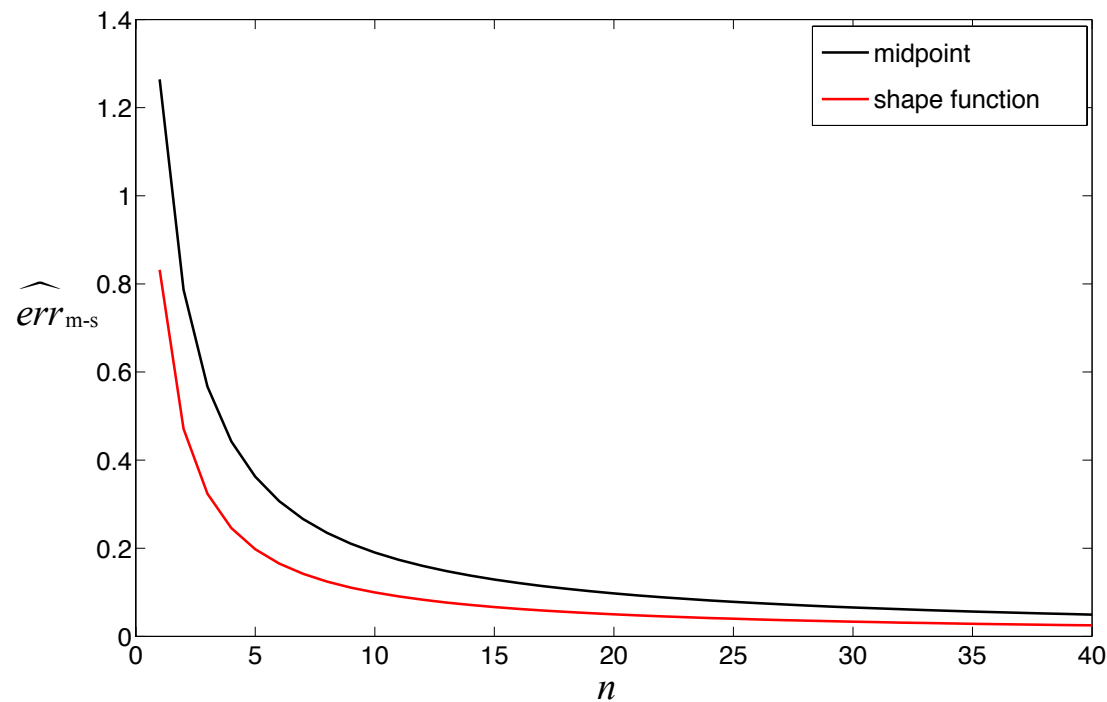


Point discretization methods

Example

Comparison of midpoint and shape function methods

Global error

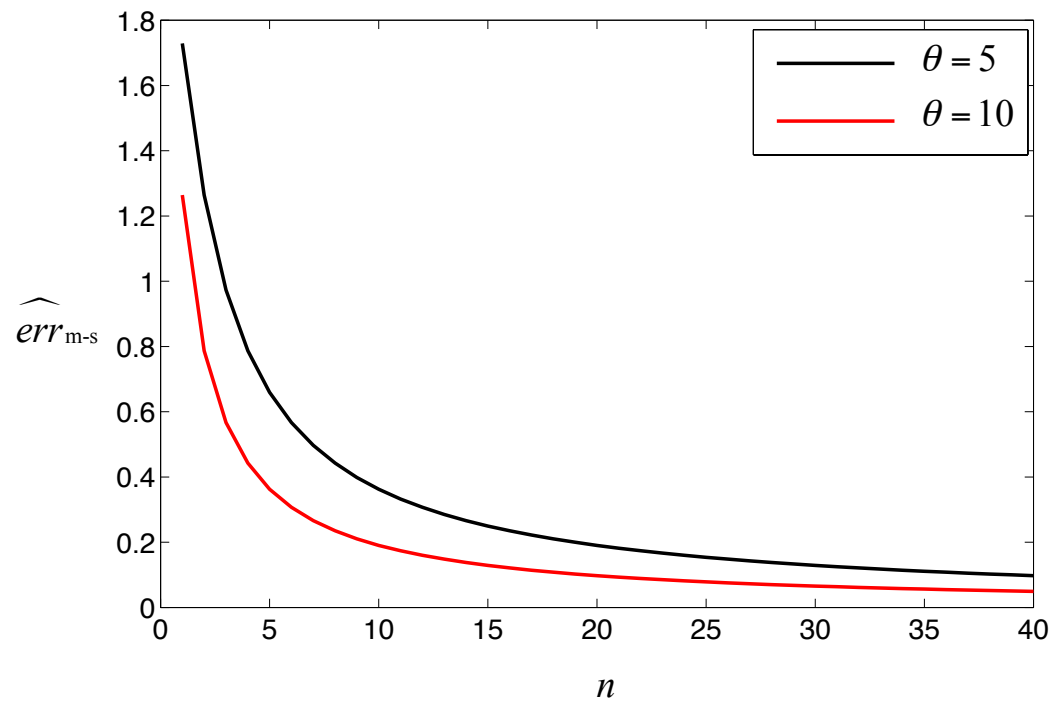


Point discretization methods

Example

Midpoint method: Influence of the scale of fluctuation θ

Global error



Karhunen-Loève expansion

Karhunen-Loève expansion of a second order random field:

$$D(z, \theta) = \mu_D(z) + \sum_{i=1}^{\infty} \sqrt{\lambda_i} \cdot \varphi_i(z) \cdot U_i(\theta)$$

Fredholm integral eigenvalue problem:

$$\int_{\Omega} \Gamma_{DD}(z_1, z_2) \varphi_i(z_2) dz_2 = \lambda_i \varphi_i(z_1) \quad \forall i = 1, 2, \dots$$

Orthogonality of eigenfunctions: $\langle \varphi_i(z), \varphi_j(z) \rangle = \int_{\Omega} \varphi_i(z) \varphi_j(z) dz = \delta_{ij}$

Spectral decomposition of the auto-covariance function:

$$\Gamma_{DD}(z_1, z_2) = \sum_{i=1}^{\infty} \lambda_i \varphi_i(z_1) \varphi_i(z_2)$$

Karhunen-Loève expansion

Random variables in the expansion

$$U_i(\theta) = \frac{1}{\sqrt{\lambda_i}} \int_{\Omega} (D(z, \theta) - \mu_D(z)) \varphi_i(z) dz$$

Properties of the random variables:

- They have zero mean: $E[U_i] = 0$
- They are orthonormal (uncorrelated, unit standard deviation) $E[U_i U_j] = \delta_{ij}$
- If $D(z, \theta)$ is Gaussian they are **independent standard normal**

Karhunen-Loève expansion

Truncated Karhunen-Loève expansion (after m largest eigenvalues and corresponding eigenfunctions):

$$D(z, \mathbf{U}) = \mu_D(z) + \sum_{i=1}^m \sqrt{\lambda_i} \cdot \varphi_i(z) \cdot U_i$$

The set of $\{\varphi_i(z)\}$ form a complete orthogonal basis in $L^2(\Omega)$ and are optimal with respect to the mean square truncation error

Karhunen-Loève expansion

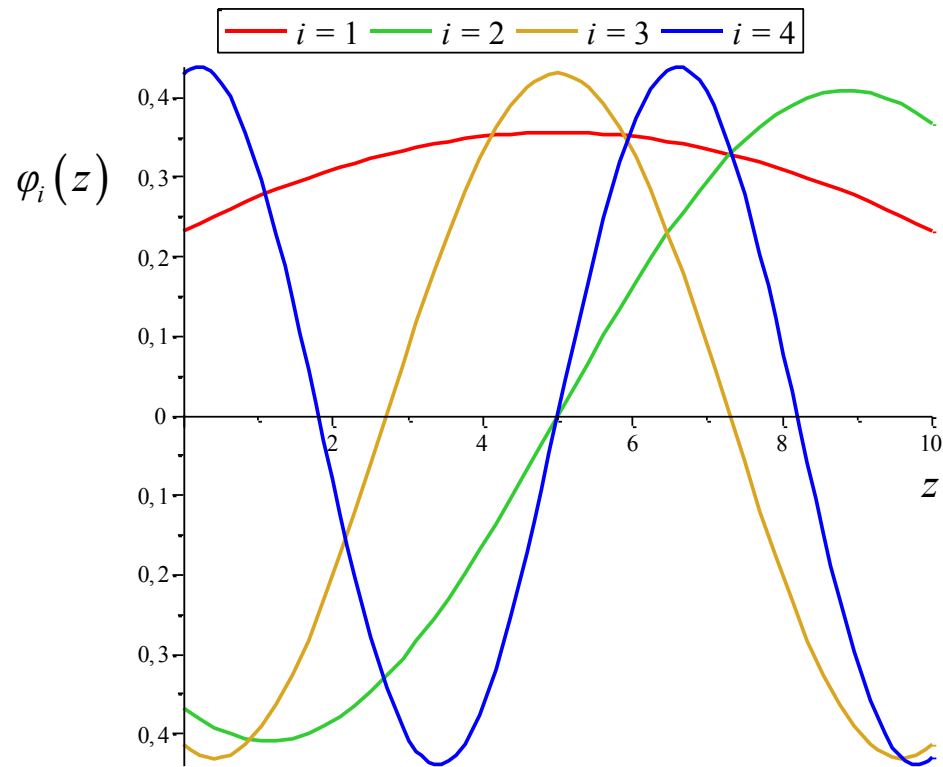
Example

- 1D homogeneous Gaussian random field in $[0, 10]$
- Autocorrelation coefficient function: $\rho(\xi) = \exp\left(-\frac{2|\xi|}{\theta}\right)$

Karhunen-Loève expansion

Example

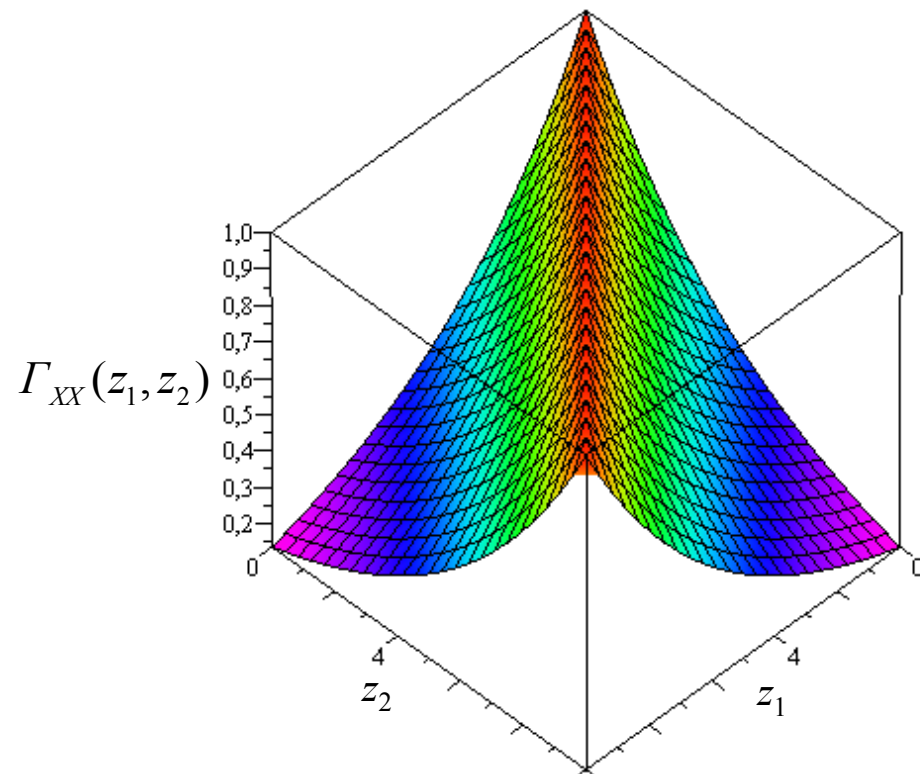
Eigenfunctions



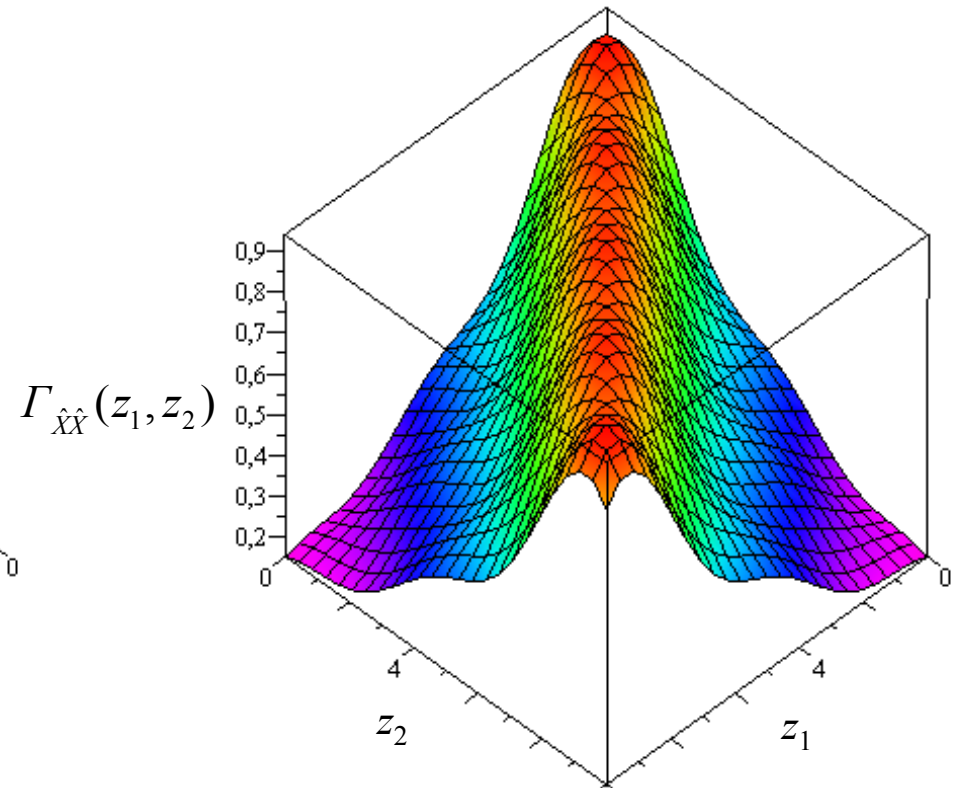
Karhunen-Loève expansion

Example

Original covariance



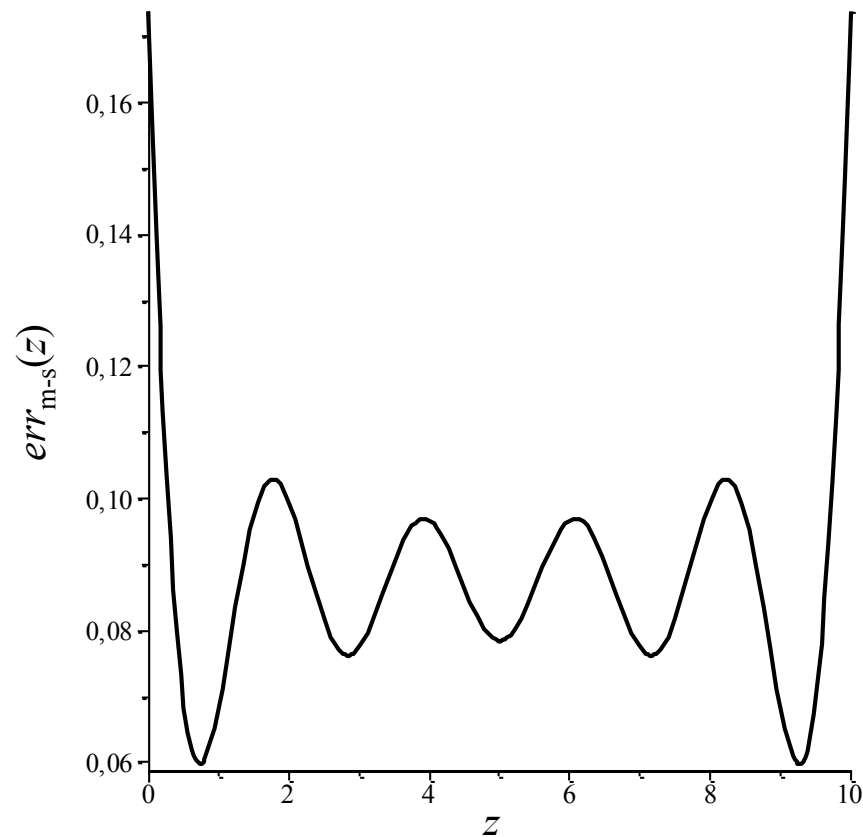
Approximation with 5 terms



Karhunen-Loève expansion

Example

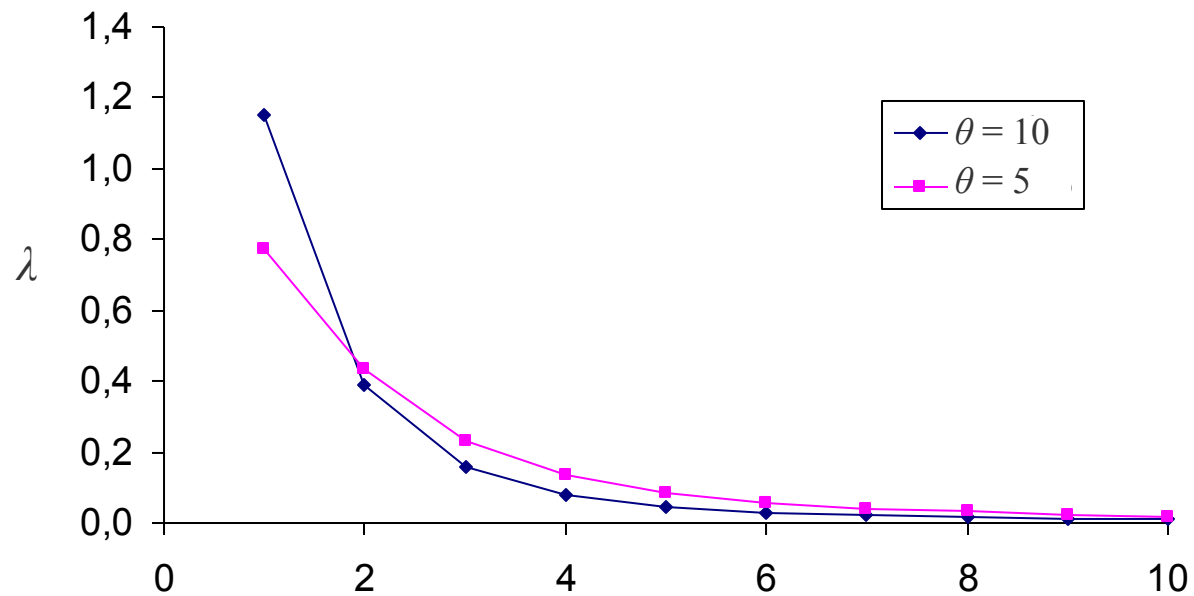
Local (point-wise) error with 5 terms



Karhunen-Loève expansion

Example

Eigenvalues – influence of scale of fluctuation θ



KL expansion of non-Gaussian random field

Marginal distribution of random field: $F_{D(z)}(x, z)$

- Express as a function of a standard Gaussian random field:

Set

$$F_{D(z)}(D(z, \theta), z) = \Phi(U(z, \theta))$$

$$\Rightarrow D(z, \theta) = F_{D(z)}^{-1}(\Phi(U(z, \theta)), z)$$

- Perform KL expansion of Gaussian random field:

$$U(z, \mathbf{U}) = \sum_{i=1}^m \sqrt{\lambda_i} \cdot \varphi_i(z) \cdot U_i$$

where

$$\int_{\Omega} \rho_{UU}(z_1, z_2) \varphi_i(z_2) dz_2 = \lambda_i \varphi_i(z_1)$$

...

KL expansion of non-Gaussian random field

...

$$\Rightarrow D(z, \mathbf{U}) = F_{D(z)}^{-1} \left[\Phi \left(\sum_{i=1}^m \sqrt{\lambda_i} \cdot \varphi_i(z) \cdot U_i \right), z \right]$$

Example: Lognormal random field

$$D(z, \theta) = \exp(\mu_U(z) + \sigma_U(z)U(z, \theta))$$

KL representation:

$$D(z, \mathbf{U}) = \exp \left(\mu_U(z) + \sigma_U(z) \sum_{i=1}^m \sqrt{\lambda_i} \cdot \varphi_i(z) \cdot U_i \right)$$

Stochastic stiffness matrix and force vector

Express random field with their KL expansion:

$$D(z, \theta) \approx D(z, \mathbf{U}) \quad q(z, \theta) \approx q(z, \mathbf{U})$$

Element stochastic stiffness matrix:

$$\mathbf{K}^e(\mathbf{U}) = \frac{1}{2h^e} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \int_{-1}^1 D(z, \mathbf{U}) d\xi$$

Element stochastic force vector:

$$\mathbf{F}^e(\mathbf{U}) = \frac{h^e}{2} \int_{-1}^1 q(z, \mathbf{U}) \begin{bmatrix} \frac{1-\xi}{2} \\ \frac{1+\xi}{2} \end{bmatrix} d\xi$$

Assemble matrices:

$$\mathbf{K}(\mathbf{U})\mathbf{u}(\mathbf{U}) = \mathbf{F}(\mathbf{U})$$