



Stochastic modelling of heterogeneous materials based on image analysis

Anna Kučerová, Jan Sýkora and Jan Zeman

Seminar on Uncertainty Modelling in Engineering

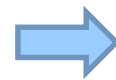


Modelling of heterogeneous materials with

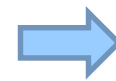
- random spatial distribution of particular constituents
- characteristic length comparable to the macroscopic lengthscale



irregular masonry



assumptions required for application of homogenization-based modelling are inadequate

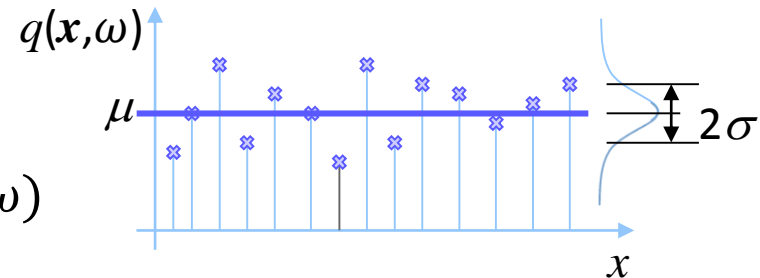


variation in material properties has significant influence on structural response and needs to be considered



Random fields

Definition of a random field $q(\mathbf{x}, \omega)$:



mean: $\mu_q(\mathbf{x}) = \mathbb{E}[q(\mathbf{x}, \omega)] = \int_{\Omega} q(\mathbf{x}, \omega) \mathbb{P}(d\omega)$

covariance function: $C_q(\mathbf{x}, \mathbf{x}') = \mathbb{E}[(q(\mathbf{x}, \omega) - \mu_q(\mathbf{x}))(q(\mathbf{x}', \omega) - \mu_q(\mathbf{x}'))] =$
 $= \int_{\Omega} (q(\mathbf{x}, \omega) - \mu_q(\mathbf{x})) (q(\mathbf{x}', \omega) - \mu_q(\mathbf{x}')) \mathbb{P}(d\omega)$

Modelling of a random field:

- discretization: by FE mesh into a finite but high number of points

covariance function $C_q(\mathbf{x}, \mathbf{x}')$ becomes covariance matrix \mathbf{C}_q

- dimensionality reduction: by solving eigenvalue problem: $\mathbf{C}_q \boldsymbol{\phi}_i = \zeta_i \boldsymbol{\phi}_i$

leads to Karhunen-Loève (KL) expansion: $\hat{q}(\omega) \approx \mu_q + \sum_{i=1}^M \sqrt{\zeta_i} \xi_i(\omega) \boldsymbol{\phi}_i$



Demonstration for a linear system: $A(q(\xi(\omega))) \mathbf{u}(\xi(\omega)) = \mathbf{f}$

- system response can be approximated by polynomial chaos (PC) with respect to probability measure of $\xi(\omega)$: $\tilde{\mathbf{u}}(\xi(\omega)) = \sum_{\alpha \in \mathcal{J}} \mathbf{u}_\alpha H_\alpha(\xi(\omega))$
e.g. Hermite polynomials $H_\alpha(\xi(\omega))$ are orthogonal in Gaussian measure

- using KL approximation of $q(\xi(\omega))$ and PC approximation of $\mathbf{u}(\xi(\omega))$:

$$\hat{A}(\hat{q}(\omega)) \tilde{\mathbf{u}}(\omega) = \mathbf{f}$$

- applying Bubnov-Galerkin projection we obtain

$$\forall \beta \in \mathcal{J}: \sum_{\alpha \in \mathcal{J}} \mathbb{E} \left[H_\beta(\xi(\omega)) \hat{A}(\hat{q}(\xi(\omega))) H_\alpha(\xi(\omega)) \right] \mathbf{u}_\alpha = \mathbb{E}(\mathbf{f} H_\beta(\xi(\omega)))$$

which is a large system of equation for PC coefficients



Covariance function

How to determine covariance function of material properties?

- Gaussian covariance function:

$$C(\mathbf{x}, \mathbf{x}') = \sigma_q^2 \exp\left(-\frac{(x-x')^2}{2L_x^2} - \frac{(y-y')^2}{2L_y^2}\right)$$

- Exponential covariance function:

$$C(\mathbf{x}, \mathbf{x}') = \sigma_q^2 \exp\left(-\left|\frac{x-x'}{L_x}\right| - \left|\frac{y-y'}{L_y}\right|\right)$$

- Image-based covariance function:

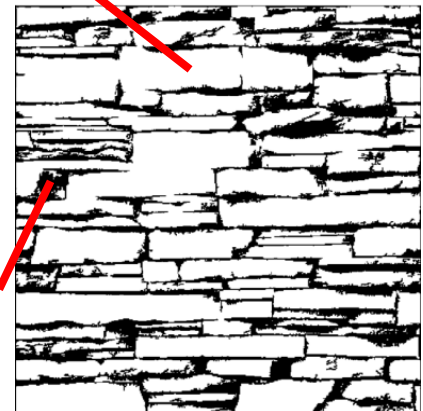
$$C(\mathbf{x}, \mathbf{x}') = \left(S_2^{(1)}(\mathbf{x}, \mathbf{x}') - (c^{(1)})^2\right) (q^{(1)} - q^{(2)})^2$$

$c^{(1)}$ is volume fraction of phase (1)

$S_2^{(1)}(\mathbf{x}, \mathbf{x}')$ is two-point probability function



$q^{(1)}$



$q^{(2)}$

[Lombardo et al., 2009]

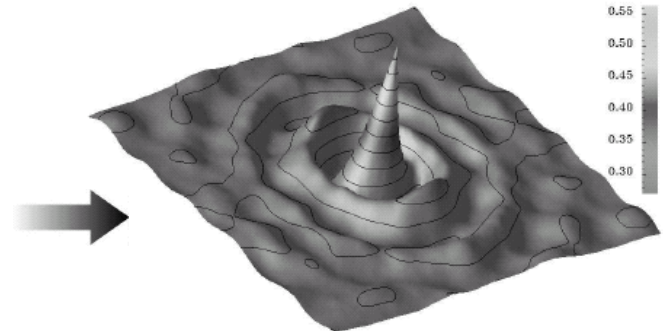
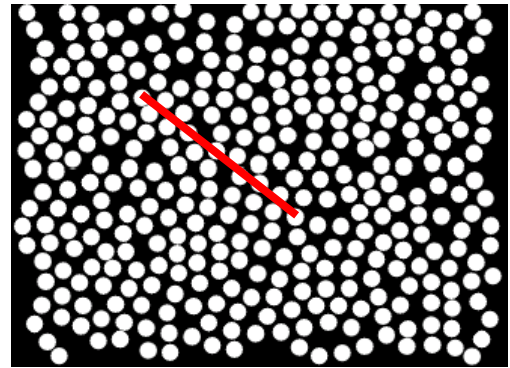


Covariance function

Two point probability function – probability that vector $\mathbf{x}\mathbf{x}'$ starts and ends in a given phase

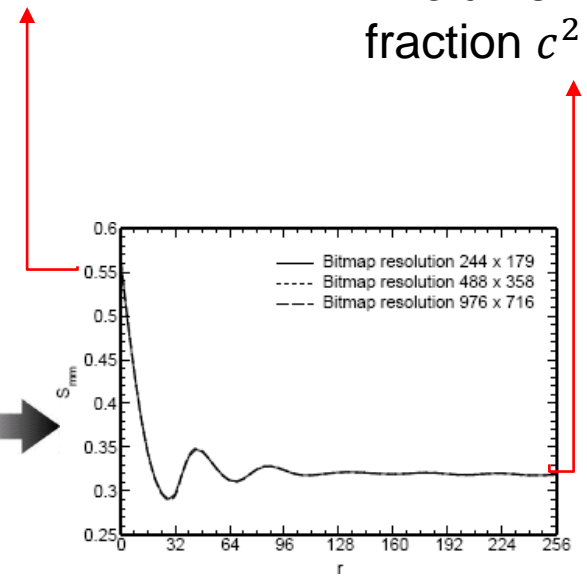
$$S_2^{(1)}(\mathbf{x}, \mathbf{x}') = \text{IDFT}\{\text{DFT}\{\chi^{(1)}(\mathbf{x}, \mathbf{x}')\} \overline{\text{DFT}\{\chi^{(1)}(\mathbf{x}, \mathbf{x}')\}}\}$$

$$\chi^{(1)}(\mathbf{x}, \omega) = \begin{cases} 1 & \text{if } \mathbf{x} \in \mathcal{D}^{(1)}(\omega) \\ 0 & \text{otherwise} \end{cases}$$



volume fraction c

squared volume fraction c^2



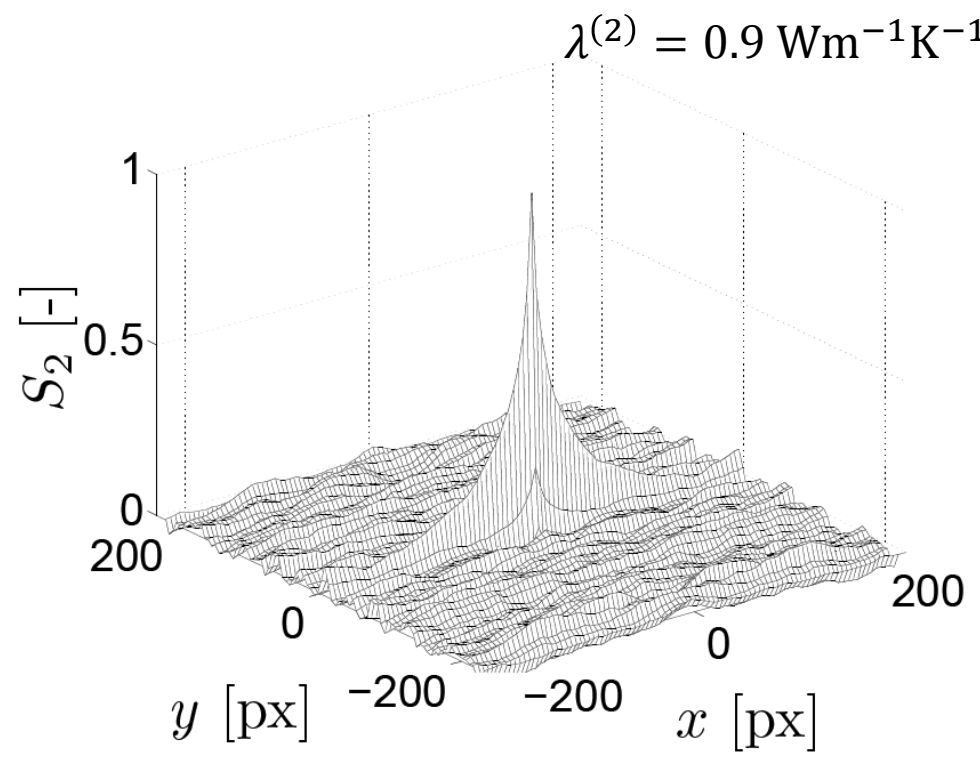


Numerical example – irregular masonry

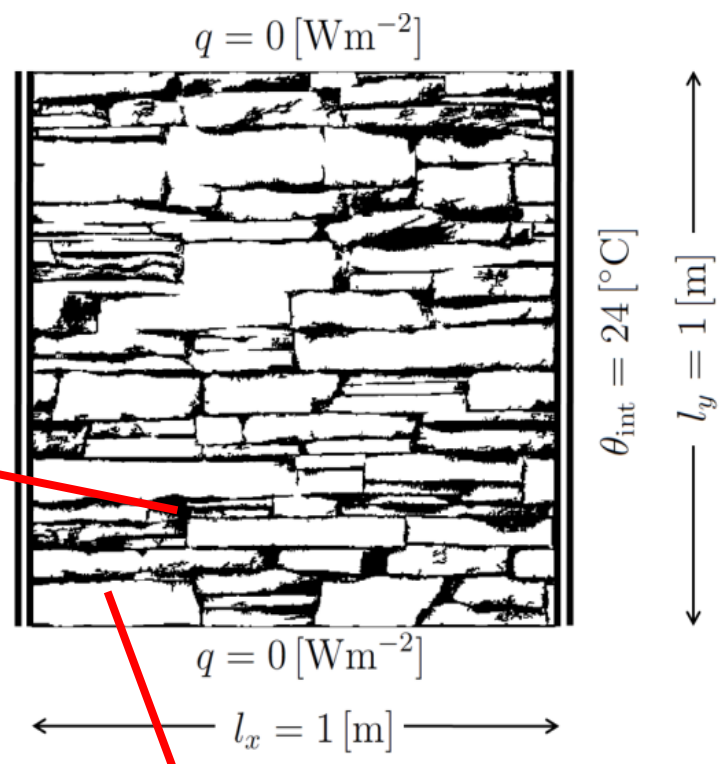
Linear heat conduction problem:

$$-\nabla \cdot (\lambda(x) \nabla \theta(x)) = f(x), \quad x \in \mathcal{G} \subset \mathbb{R}^2$$

$$\theta(x) = g(x), \quad x \in \partial \mathcal{G},$$



$\lambda^{(2)} = 0.9 \text{ Wm}^{-1} \text{ K}^{-1}$



$q = 0 \text{ [Wm}^{-2}\text{]}$

$\theta_{\text{ext}} = 5 \text{ [}^\circ\text{C]}$

$\theta_{\text{int}} = 24 \text{ [}^\circ\text{C]}$

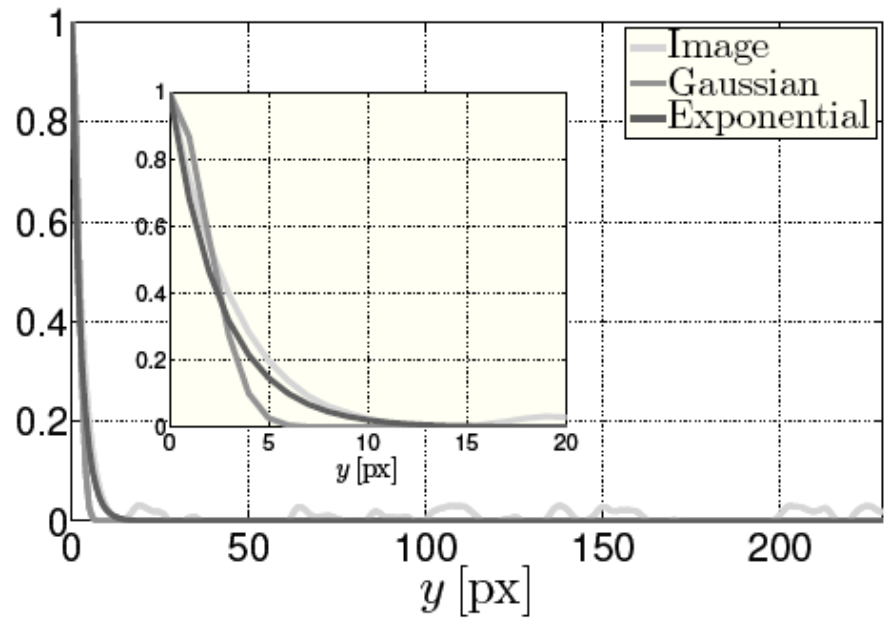
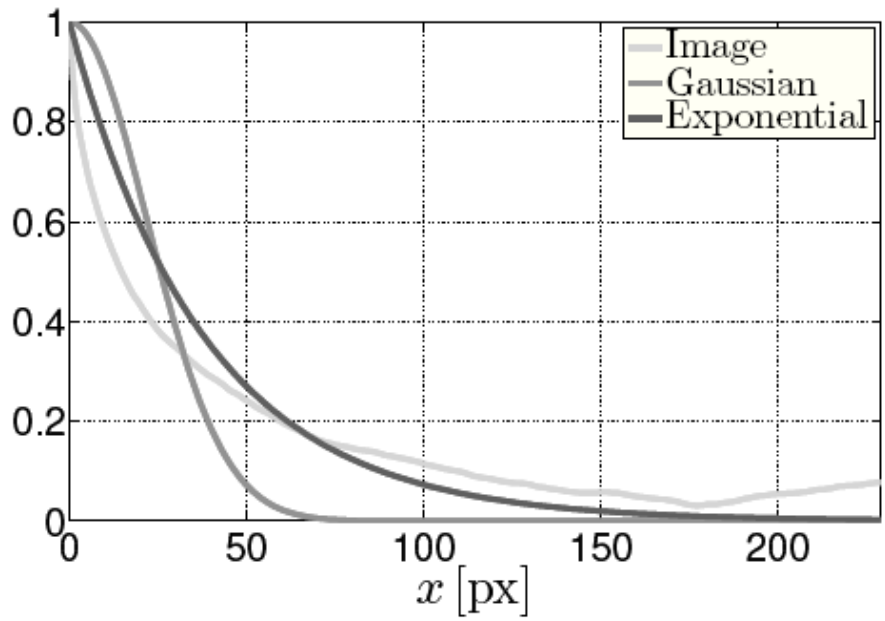
$l_x = 1 \text{ [m]}$

$l_y = 1 \text{ [m]}$

$\lambda^{(1)} = 1.9 \text{ Wm}^{-1} \text{ K}^{-1}$



Numerical example – covariance kernel

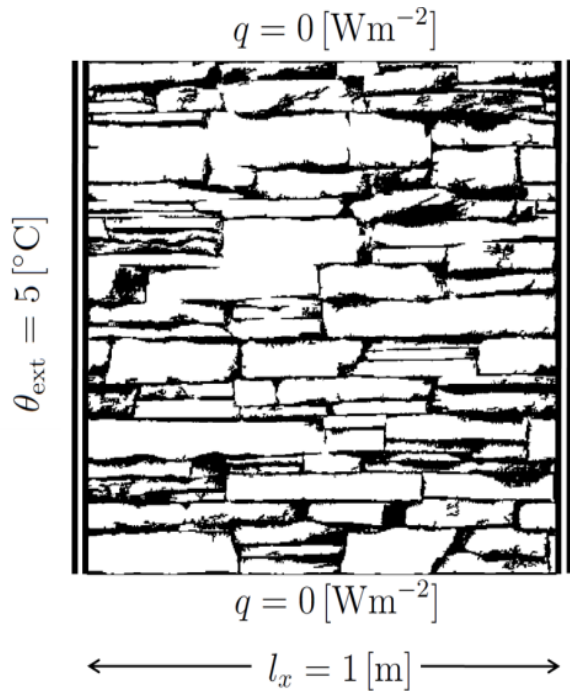


Correlation lengths of Gaussian and exponential covariance function were optimized so as to fit the corresponding covariance functions to image-based covariance function:

type	L_x	L_y
Gaussian	0.047552	0.004067
Exponential	0.083288	0.005689



Numerical example – FE discretization

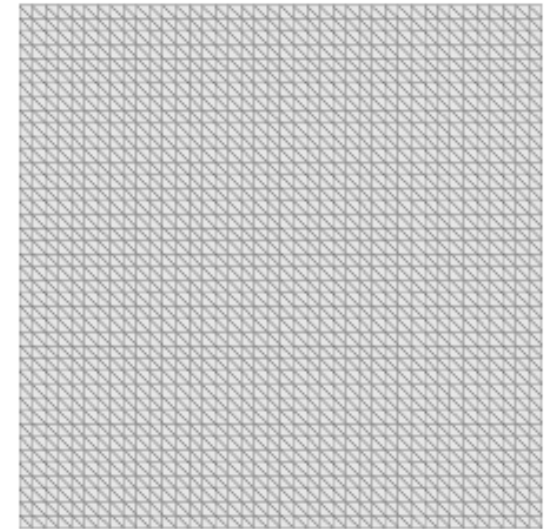


$\theta_{\text{int}} = 24 \text{ [}^\circ\text{C]}$

$l_y = 1 \text{ [m]}$



Element size
= 0.2 [m],
(36 FE nodes)

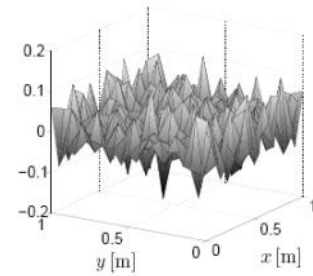
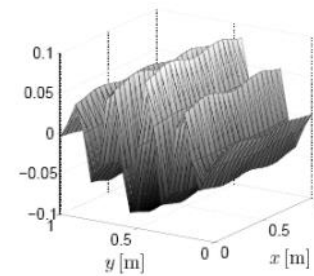
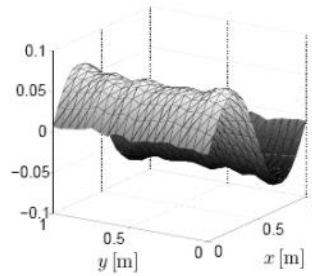
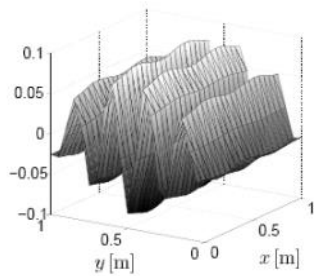
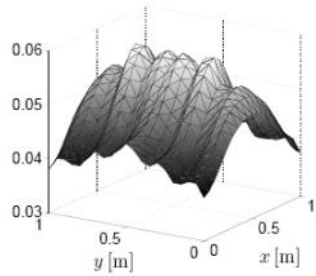


Element size
= 0.025 [m],
(1681 FE nodes)

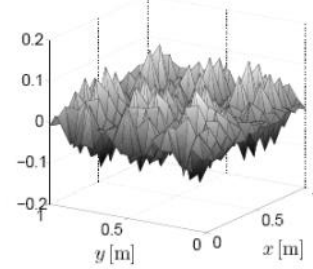
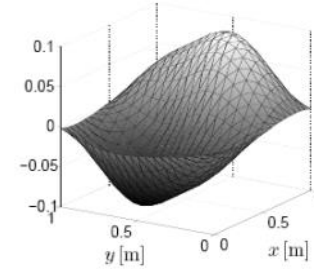
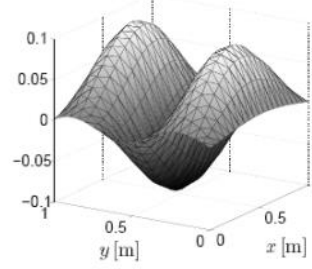
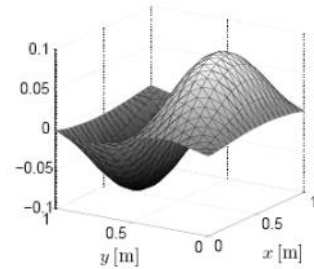
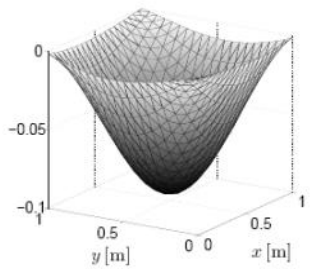


Numerical example – Karhunen-Loève modes

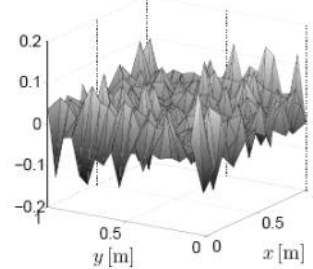
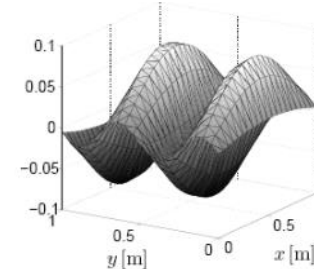
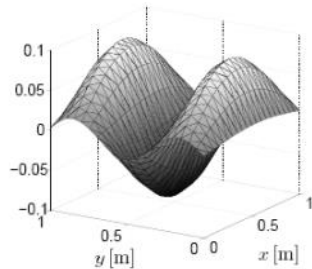
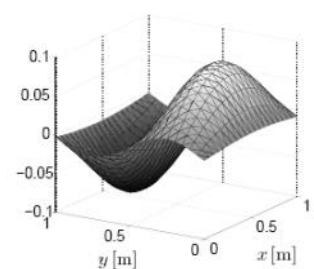
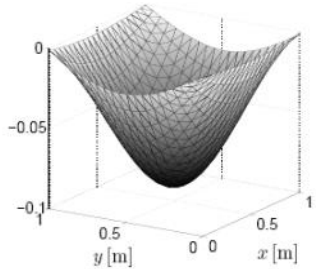
Image CF



Gaussian CF



Exponential CF



$M = 1$

$M = 2$

$M = 3$

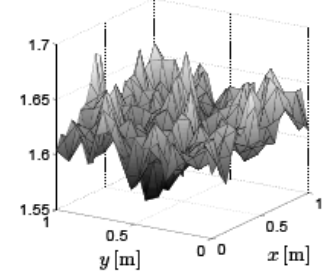
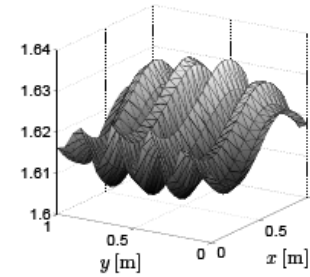
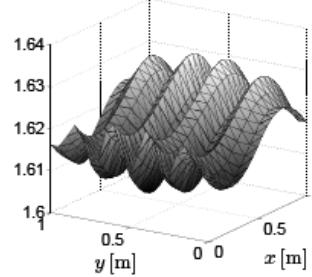
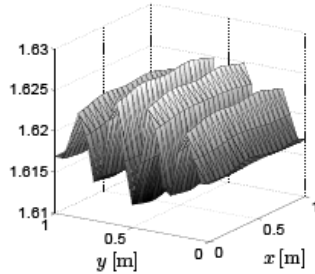
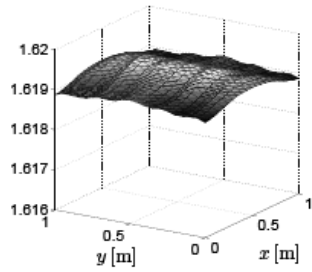
$M = 4$

$M = 441$

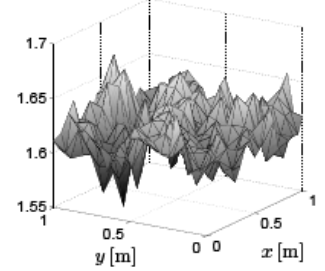
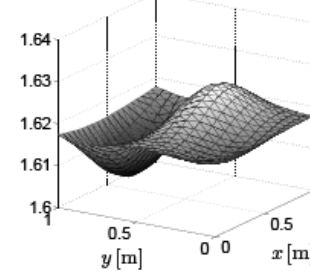
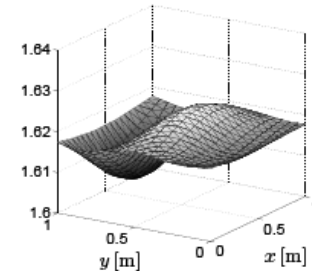
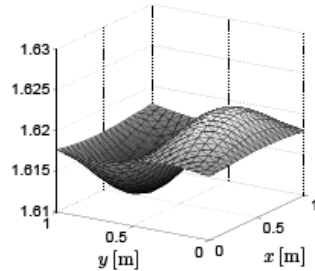
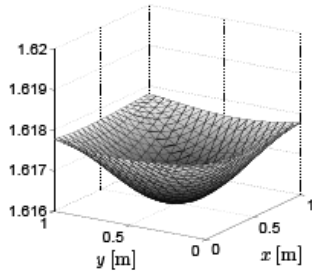


Numerical example – RF realisations

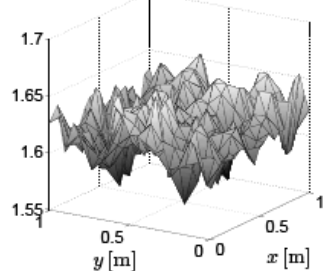
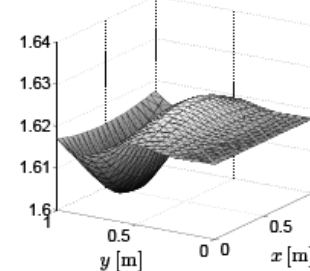
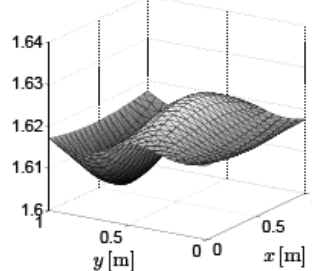
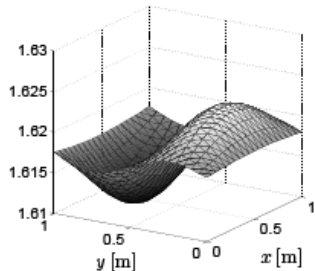
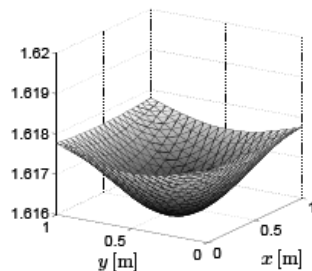
Image CF



Gaussian CF



Exponential CF



$M = 1$

$M = 2$

$M = 3$

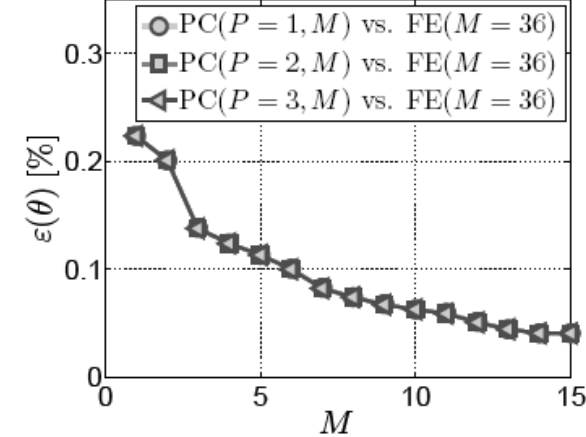
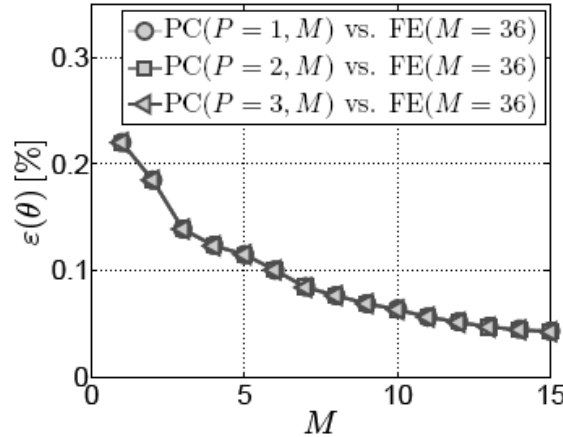
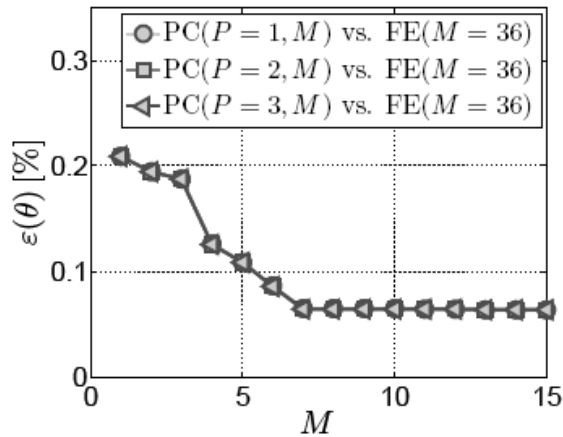
$M = 4$

$M = 441$



Numerical example – PC + KL error

ES = 0.200 [m]



ES = 0.025 [m]

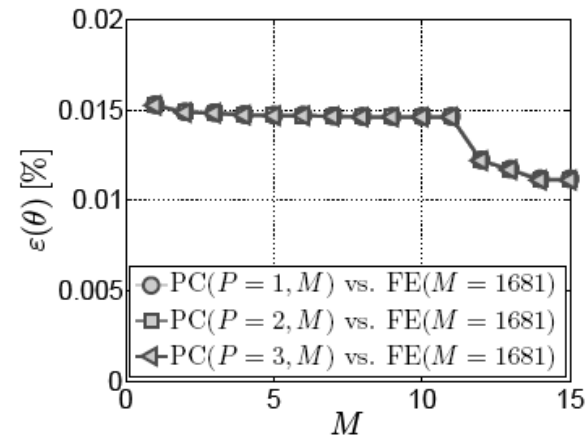
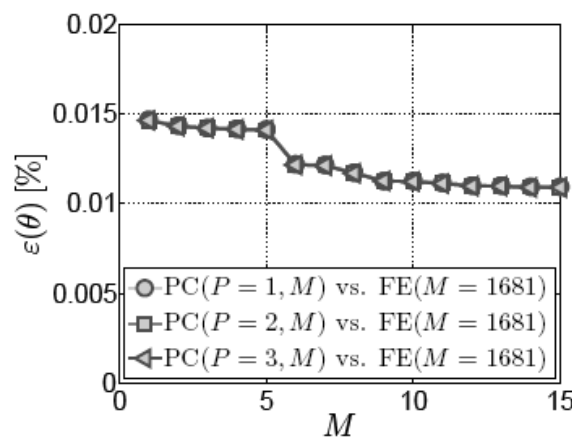
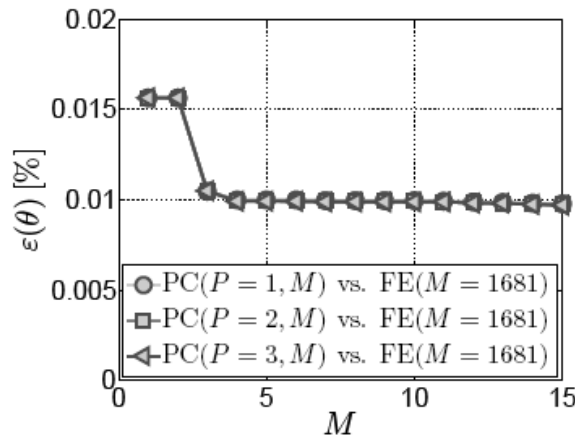


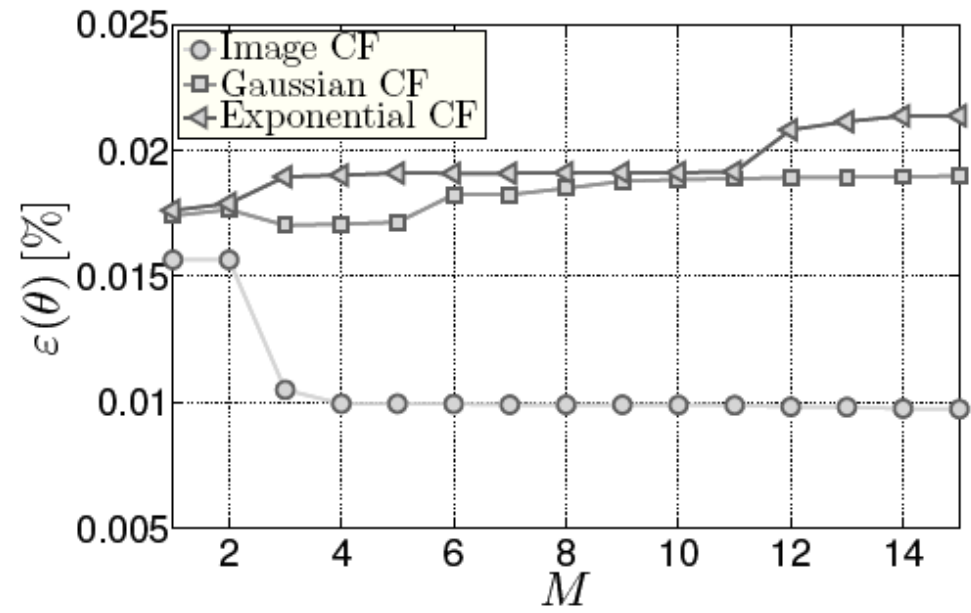
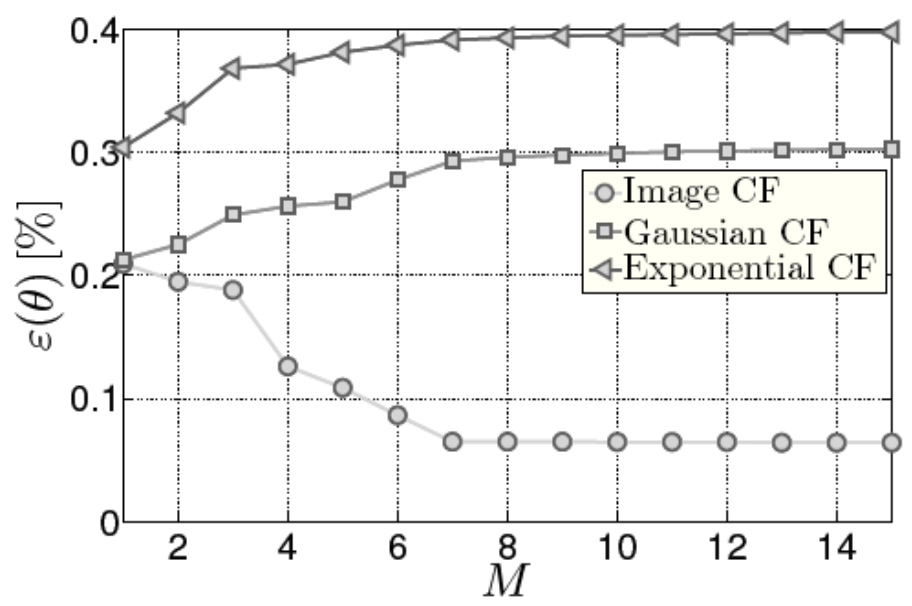
Image CF

Gaussian CF

Exponential CF



Numerical example – Difference in CF



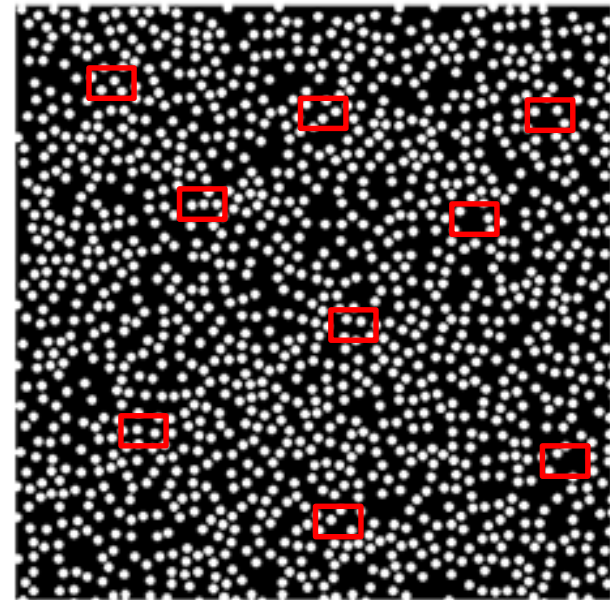
$$\epsilon(\theta) = \frac{\|\theta_M - \theta_{441}^{\text{image}}\|_{l^2(\mathcal{G} \times \Omega)}}{\|\theta_{441}^{\text{image}}\|_{l^2(\mathcal{G} \times \Omega)}}$$

Discretized by 1000 samples



Conclusions and future work

- Demonstrated significant difference in temperature field modelled using ad-hoc chosen covariance function and image-based covariance function
- Hard to determine, which covariance function truly better represents the reality → comparison needs to be done on samples randomly cut from a microstructure





Conclusions

THANK YOU FOR YOUR ATTENTION.

Aknowledgements

GAČR: projects No. 105/11/P370 and 105/12/1146