11th. World Congress on Computational Mechanics (WCCM XI)
5th. European Conference on Computational Mechanics (ECCM V)
6th. European Conference on Computational Fluid Dynamics (ECFD VI)
July 20 - 25, 2014, Barcelona, Spain

# Scale-space Based Multiscale Random Field Modelling with Local Pattern Matching

**Sönke Klostermann[1]*, Dietmar Vogt[2], Otto von Estorff[3]**

[1] EADS Innovation Works, Neßpriel 1 21129 Hamburg, soenke.klostermann@eads.net
[2] EADS Innovation Works, Neßpriel 1 21129 Hamburg, dietmar.vogt@eads.net
[3] Institute of Modelling and Computation, Hamburg University of Technology, Denickestraße 17
21073 Hamburg, estorff@tuhh.de

**Key Words:** *Random Fields, Structured Morphologies, Multiscale Transformation, Pattern Matching, Cluster Analysis, Monte Carlo Methods.*

System behaviour is influenced by a high number of uncertainties. A common distinction is made between epistemic and aleatoric uncertainty. A key source of aleatoric uncertainty is the scatter of physical system characteristics and boundary conditions. These can be subdivided into scatter of: geometry (tolerances in shape or measure), material properties (density, Young's modulus), loads and initial and boundary conditions (forces, initial velocities) [3].

For a more reliable prediction of system behaviour by means of simulation, probabilistic models can be created that account for aleatoric uncertainties by modelling individual aspects of the system and the environment as a realization of stochastic influences. For a consideration of local effects the uncertainties can be modelled by so called random fields. For a random field the parameter is a function of the position vector in the n-dimensional feature space.

Random fields describing geometry, loads or material properties may possess a highly complex structure (e. g. aerodynamic loads, composites with various fibre orientations). For the parameterisation of highly structured morphologies five general constraints can be identified [1]: similarity, structure preservation, locality, reversibility and comparability.

A simulative investigation via Monte Carlo approach requires an efficient modelling methodology as one stochastic simulation can incorporate a high number of single simulation runs. This paper shows a new method to describe random fields by a set of parameters that enables to synthesise samples for e. g. a Monte Carlo simulation. These samples have all the relevant characteristics of the original source but show a certain amount of local randomness to account for natural scatter.

The parameterisation process is based on a multi-scale pattern recognition approach that is based on the so called scale-space theory [2]. The process is based upon a convolution with a Gaussian filter on multiple scales. The multi-scale approach enables for a detection of features of different orders of magnitude (e. g. micro to macro-scale). For each scale a blob detection finds the relevant features leading to a set of parameters. By means of an optimisation approach each blob's parameters are optimised for a better approximation of the filtered signal, leading to a more compact parameter set than previous approaches [1].

For finer scales a filter-based approach is used to account for fine structured features [4]. By means of a principal component analysis the dimensionality is reduced while maintaining a good representation of features. A clustering approach is used to identify commonalities and self-similarities within single samples as well as across the samples of a set.

Firstly, that approach yields underlying information about the measured sample set: The identified stochastic model reveals »hot spots« of the whole sample population supporting a targeted design improvement, for example. Secondly, the stochastic model enables for synthesised samples. By means of a stochastic simulation we can directly predict e. g. product quality, robustness and reliability with these fully virtual prototypes.

## REFERENCES


[1] Klostermann, S. ; Lippert, S. ; Estorff, O. v.: Pattern recognition based multiscalar random field modelling. In: Sas, P.; Moens, D.; Jonckheere, S. (Hrsg.): *Proceedings of the International Conference on Uncertainty in Structural Dynamics USD2012*, S. 4999–5013

[2] Lindeberg, T.: *Scale-space theory in computer vision*. Boston: Kluwer Academic, 1994

[3] Marczyk, J.: *Principles of Simulation-Based Computer-Aided Engineering*. Barcelona: FIM Publications, 1999

[4] Zhang, T.: *Filter-Based Training Pattern Classification for Spatial Pattern Simulation*, Stanford University, Department of Geological and Environmental Sciences, Dissertation, 2006