



Bayesian inverse problems : fundamentals and engineering applications /

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editor

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Monografía

"This book is intended to provide a bottom-up and fundamental understanding of the use of probabilistic methods and reliability analysis techniques in engineering applications. It covers from the fundamentals of the theory to real life applications in the field"--

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Contenido: Cover -- Title Page -- Copyright Page -- Dedication -- Preface -- Table of Contents -- List of Figures -- List of Tables -- Contributors -- Part I Fundamentals -- 1. Introduction to Bayesian Inverse Problems -- 1.1 Introduction -- 1.2 Sources of uncertainty -- 1.3 Formal definition of probability -- 1.4 Interpretations of probability -- 1.4.1 Physical probability -- 1.4.2 Subjective probability -- 1.5 Probability fundamentals -- 1.5.1 Bayes' Theorem -- 1.5.2 Total probability theorem -- 1.6 The Bayesian approach to inverse problems -- 1.6.1 The forward problem -- 1.6.2 The inverse problem -- 1.7 Bayesian inference of model parameters -- 1.7.1 Markov Chain Monte Carlo methods -- 1.7.1.1 Metropolis-Hasting algorithm -- 1.8 Bayesian model class selection -- 1.8.1 Computation of the evidence of a model class -- 1.8.2 Information-theory approach to model-class selection -- 1.9 Concluding remarks -- 2. Solving Inverse Problems by Approximate Bayesian Computation -- 2.1 Introduction to the ABC method -- 2.2 Basis of ABC using Subset Simulation -- 2.2.1 Introduction to Subset Simulation -- 2.2.2 Subset Simulation for ABC -- 2.3 The ABC-SubSim algorithm -- 2.4 Summary -- 3. Fundamentals of Sequential System Monitoring and Prognostics Methods -- 3.1 Fundamentals -- 3.1.1 Prognostics and SHM -- 3.1.2 Damage response modelling -- 3.1.3 Interpreting uncertainty for prognostics -- 3.1.4 Prognostic performance metrics -- 3.2 Bayesian tracking methods -- 3.2.1 Linear Bayesian Processor: The Kalman Filter -- 3.2.2 Unscented Transformation and Sigma Points: The Unscented Kalman Filter -- 3.2.3 Sequential Monte Carlo methods: Particle Filters -- 3.2.3.1 Sequential

importance sampling -- 3.2.3.2 Resampling -- 3.3 Calculation of EOL and RUL -- 3.3.1 The failure prognosis problem -- 3.3.2 Future state prediction -- 3.4 Summary

4. Parameter Identification Based on Conditional Expectation -- 4.1 Introduction -- 4.1.1 Preliminaries-basics of probability and information -- 4.1.1.1 Random variables -- 4.1.2 Bayes' theorem -- 4.1.3 Conditional expectation -- 4.2 The Mean Square Error Estimator -- 4.2.1 Numerical approximation of the MMSE -- 4.2.2 Numerical examples -- 4.3 Parameter identification using the MMSE -- 4.3.1 The MMSE filter -- 4.3.2 The Kalman filter -- 4.3.3 Numerical examples -- 4.4 Conclusion -- Part II Engineering Applications -- 5. Sparse Bayesian Learning and its Application in Bayesian System Identification -- 5.1 Introduction -- 5.2 Sparse Bayesian learning -- 5.2.1 General formulation of sparse Bayesian learning with the ARD prior -- 5.2.2 Bayesian Ockham's razor implementation in sparse Bayesian learning -- 5.3 Applying sparse Bayesian learning to system identification -- 5.3.1 Hierarchical Bayesian model class for system identification -- 5.3.2 Fast sparse Bayesian learning algorithm -- 5.3.2.1 Formulation -- 5.3.2.2 Proposed fast SBL algorithm for stiffness inversion -- 5.3.2.3 Damage assessment -- 5.4 Case studies -- 5.5 Concluding remarks -- Appendices -- Appendix A: Derivation of MAP estimation equations for (Sa(B and (Sb(B -- 6. Ultrasonic Guided-waves Based Bayesian Damage Localisation and Optimal Sensor Configuration -- 6.1 Introduction -- 6.2 Damage localisation -- 6.2.1 Time-frequency model selection -- 6.2.1.1 Stochastic embedding of TF models -- 6.2.1.2 Model parameters estimation -- 6.2.1.3 Model class assessment -- 6.2.2 Bayesian damage localisation -- 6.2.2.1 Probabilistic description of ToF model -- 6.2.2.2 Model parameter estimation -- 6.3 Optimal sensor configuration -- 6.3.1 Value of information for optimal design -- 6.3.2 Expected value of information -- 6.3.2.1 Algorithmic implementation -- 6.4 Summary

7. Fast Bayesian Approach for Stochastic Model Updating using Modal Information from Multiple Setups -- 7.1 Introduction -- 7.2 Probabilistic consideration of frequency-domain responses -- 7.2.1 PDF of multivariate FFT coefficients -- 7.2.2 PDF of PSD matrix -- 7.2.3 PDF of the trace of the PSD matrix -- 7.3 A two-stage fast Bayesian operational modal analysis -- 7.3.1 Prediction error model connecting modal responses and measurements -- 7.3.2 Spectrum variables identification using FBSTA -- 7.3.3 Mode shape identification using FBSDA -- 7.3.4 Statistical modal information for model updating -- 7.4 Bayesian model updating with modal data from multiple setups -- 7.4.1 Structural model class -- 7.4.2 Formulation of Bayesian model updating -- 7.4.2.1 The introduction of instrumental variables system mode shapes -- 7.4.2.2 Probability model connecting 'system mode shapes' and measured local mode shape -- 7.4.2.3 Probability model for the eigenvalue equation errors -- 7.4.2.4 Negative log-likelihood function for model updating -- 7.4.3 Solution strategy -- 7.5 Numerical example -- 7.5.1 Robustness test of the probabilistic model of trace of PSD matrix -- 7.5.2 Bayesian operational modal analysis -- 7.5.3 Bayesian model updating -- 7.6 Experimental study -- 7.6.1 Bayesian operational modal analysis -- 7.6.2 Bayesian model updating -- 7.7 Concluding remarks -- 8. A Worked-out Example of Surrogate-based Bayesian Parameter and Field Identification Methods -- 8.1 Introduction -- 8.2 Numerical modelling of seabed displacement -- 8.2.1 The deterministic computation of seabed displacements -- 8.2.2 Modified probabilistic formulation -- 8.3 Surrogate modelling -- 8.3.1 Computation of the surrogate by orthogonal projection -- 8.3.2 Computation of statistics -- 8.3.3 Validating surrogate models -- 8.4 Efficient representation of random fields 8.4.1 Karhunen-Loève Expansion (KLE) -- 8.4.2 Proper Orthogonal Decomposition (POD) -- 8.5 Identification of the compressibility field -- 8.5.1 Bayes' Theorem -- 8.5.2 Sampling-based procedures-the MCMC method -- 8.5.3 The Kalman filter and its modified versions -- 8.5.3.1 The Kalman filter -- 8.5.3.2 The ensemble Kalman filter -- 8.5.3.3 The PCE-based Kalman filter -- 8.5.4 Non-linear filters -- 8.6 Summary, conclusion, and outlook -- Appendices -- Appendix A: FEM computation of seabed displacements -- Appendix B: Hermite polynomials -- B.1 Generation of Hermite Polynomials -- B.2 Calculation of the norms -- B.3 Quadrature points and weights -- Appendix C: Galerkin solution of the Karhunen Loève eigenfunction problem -- Appendix D: Computation of the PCE Coefficients by Orthogonal projection -- Bibliography -- Index

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