

Time-Frequency Based Adaptive Learning for Structural Health Management

by

Debejyo Chakraborty

A Dissertation Presented in Partial Fulfillment  
of the Requirements for the Degree  
Doctor of Philosophy

ARIZONA STATE UNIVERSITY

August 2010

Time-Frequency Based Adaptive Learning for Structural Health Management

by

Debejyo Chakraborty

has been approved

July 2010

Graduate Supervisory Committee:

Antonia Papandreou-Suppappola, Chair

Aditi Chattopadhyay

Chaitali Chakrabarti

Bahar Jalali-Farahani

ACCEPTED BY THE GRADUATE COLLEGE

## ABSTRACT

In the last few decades, several statistical signal processing techniques have been used to deal with uncertainty when detecting, identifying and classifying structural damage. One of the key challenges in integrating signal processing techniques in real-world structural health management systems is how to incorporate diversity in the damage state and variability in environmental and operational conditions. While conventional learning methods are adequate for characterizing the underlying mechanism of damage nucleation and evolution, they are of limited use in highly complex and rapidly changing environments. This is especially the case when the amount of available data is insufficient.

In this dissertation, time-frequency based methods and hidden Markov model based methods are used for the detection and classification of structural damage. Time-frequency techniques are also used to extract damage features; these techniques are chosen as they are well-matched to the time-varying spectral characteristics of waveforms measured using sensors on the structures. The proposed methodologies are adaptively learned by allowing the stochastic models to continuously evolve from experience with the time-varying environment. Damage-related features extracted from periodically-buffered structural data are modeled using Dirichlet process mixture models that provide for a growing number of mixture components or damage classes. Coupled with input from physics-based models in a Bayesian filtering framework, the adaptively-identified classes can be traced to different types of damage. An active data selection technique is used to optimize the adaptive identification of damage classes. The proposed adaptive learning methodology is baseline-free in the sense that it does not require any a priori damage training.

A novel information-transfer learning methodology is also proposed that reuses param-

eters that are learned from similar previous experiments. An inductive transfer mechanism is considered to aid damage classification when the available training data is statistically insufficient.

*To*

*my parents, Sulagna & Debashis Chakraborty*

*for their wonderful parenting, guidance, support and care,*

*and*

*my wife, Bhavana Chakraborty*

*for her love and persistent encouragement.*

## ACKNOWLEDGMENTS

I extend my thanks and gratitude to my advisor, Prof. Antonia Papandreou-Suppappola for her continued guidance, support and mentoring. I am also very grateful for the mentoring of Dr. Narayan Kovvali and his invaluable collaboration.

I would like to thank Prof. Aditi Chattopadhyay, Prof. Pedro Peralta, Dr. Jun Wei, Dr. Sunilkumar Soni and Dr. Subhasish Mohanty from the School of Mechanical, Aerospace, Chemical and Materials Engineering at Arizona State University for providing me with Lamb wave data from bolted joint and lug samples, as well as the finite-element analysis model that I used in this work.

I would like to also thank Prof. James Spicer and Lindsey Channels from the Department of Materials Science and Engineering, at John Hopkins University for providing me with ultrasonic data and M. Derriso, M. DeSimio and S. Olson (AFRL, Wright Patterson AFB) for providing me with fastener failure data from a square aluminum plate.

I am thankful to my committee members, Prof. Chaitali Chakrabarti, Prof. Bahar Jalali-Farahani, Prof. Aditi Chattopadhyay and Prof. Andreas Spanias for their invaluable comments and constructive criticism.

I thank my family for their support and inspiration.

This work was supported by the Department of Defense Air Force Office of Scientific Research Grant FA95550-06-1-0309 (former program manager: Dr. Victor Giurgiutiu and current program manager: Dr. David S. Stargel).

## TABLE OF CONTENTS

	Page
LIST OF TABLES . . . . .	xii
LIST OF FIGURES . . . . .	xiii
CHAPTER	
1 INTRODUCTION . . . . .	1
1.1. Structural Health Monitoring . . . . .	1
1.2. Processing of Signals for Structural Health Monitoring . . . . .	2
1.3. Proposed Matched Time-frequency Processing for Structural Health Monitoring . . . . .	5
1.4. Proposed Adaptive Learning Processing for SHM . . . . .	5
1.5. Dissertation Organization . . . . .	7
1.6. List of Acronyms Used in Dissertation . . . . .	8
1.7. Notations . . . . .	10
2 SIGNAL PROCESSING METHODS IN STRUCTURAL HEALTH MONITORING . . . . .	17
2.1. Time Domain Analysis . . . . .	17
2.2. Acoustic Emission . . . . .	17
2.3. Ultrasonics . . . . .	18
2.4. Kurtosis . . . . .	18
2.5. Cepstrum analysis . . . . .	19
2.6. Guided Waves . . . . .	19
2.7. Electromagnetic Impedance . . . . .	20

CHAPTER	Page
2.8. Fourier Transform Component Pair . . . . .	20
2.9. Wavelet Transform . . . . .	21
2.10. Correlation . . . . .	21
3 TIME-FREQUENCY DAMAGE CLASSIFICATION . . . . .	23
3.1. Matching Pursuit Decomposition based Feature Extraction . . . . .	23
3.2. Matching Pursuit Decomposition based Time-Frequency Representation . .	26
3.2.1. Demonstration of the MPD algorithm and MPD-TFR . . . . .	28
3.3. Matching Pursuit Decomposition based Damage Classification . . . . .	29
3.3.1. Classification Using MPD . . . . .	29
3.3.2. Modified MPD Classifier . . . . .	31
3.4. Time-frequency based Classification of Structural Data using Lamb Wave Sensing . . . . .	35
3.4.1. Experimental Setup and Data Collection . . . . .	35
3.4.2. Data Preprocessing and MPD . . . . .	37
3.4.3. Optimizing the MPD-TFR Classifier . . . . .	41
3.4.4. MMPD and Dictionary Size . . . . .	43
3.4.5. Classification Results . . . . .	44
3.5. Bayesian Sensor Fusion . . . . .	49
3.6. Ultrasonic Measurement and MMPD Classifier . . . . .	51
3.6.1. Experimental setup and data collection . . . . .	51
3.6.2. Preprocessing . . . . .	54

CHAPTER	Page
3.6.3. MMPD Classifier and Choice of Parameters . . . . .	54
3.6.4. Classification Results . . . . .	56
4 HIDDEN MARKOV MODEL BASED DAMAGE CLASSIFICATION . . . . .	58
4.1. Hidden Markov Models . . . . .	58
4.2. Model Selection and Variational Bayesian Learning . . . . .	59
4.3. HMM Based Damage Classifier . . . . .	62
4.4. Variational Bayes for Estimating Number of HMM States . . . . .	63
4.5. Comparing HMM and MPD-TFR Damage Classification . . . . .	64
4.5.1. Time-Frequency Feature Extraction using MPD . . . . .	64
4.5.2. Experimental Setup and Data Collection . . . . .	65
4.5.3. Choice of Model Parameters . . . . .	65
4.5.4. Classification Results . . . . .	67
4.6. Noise Performance . . . . .	70
4.6.1. Data Synthesis and Feature Extraction . . . . .	70
4.6.2. Choice of Parameters for the Discrete HMM Classifier . . . . .	75
4.6.3. Classification Result . . . . .	76
5 ADAPTIVE LEARNING USING MARKOV CHAIN MONTE CARLO & ESTI- MATION OF PROGRESSIVE DAMAGE . . . . .	79
5.1. Markov Chain Monte Carlo . . . . .	80
5.1.1. Markov Chain Monte Carlo Integral . . . . .	80
5.1.2. Gibbs Sampler . . . . .	84

CHAPTER	Page
5.2. Learning and Inference via Markov Chain Monte Carlo . . . . .	86
5.2.1. Dirichlet Process . . . . .	87
5.2.2. Stick Breaking Prior . . . . .	89
5.2.3. Dirichlet Process Mixture Model . . . . .	89
5.2.4. Pólya Urn Gibbs Sampler for Dirichlet Process . . . . .	90
5.2.5. Blocked Gibbs Sampler . . . . .	94
5.3. Learning Gaussian Mixture Model using Markov Chain Monte Carlo . . . . .	96
5.4. Adaptive Learning Framework for Progressive Damage Estimation . . . . .	100
5.4.1. Matching Pursuit Decomposition based Probability Density Function	102
5.4.2. Statistical Measure of Similarity . . . . .	103
5.4.3. Minimum Discrepancy Uniform Reference Feature Selection . . . . .	105
5.4.4. Progressive Clustering Using Adaptive Learning . . . . .	108
5.4.5. Bayesian Filtering . . . . .	109
5.5. Adaptive Estimation of Fatigue Crack Damage in Compact Tension Sample	115
5.5.1. Experimental Setup and Data Collection . . . . .	115
5.5.2. Results . . . . .	117
6 TRANSFER LEARNING BASED REDUCED TRAINING DAMAGE CLASSI- FICATION . . . . .	122
6.1. Background . . . . .	122
6.2. Formulation of Transfer Learning Methodology . . . . .	123
6.3. Application of Transfer Learning Methodology . . . . .	125

CHAPTER	Page
7 CONCLUSION AND FUTURE DIRECTIONS . . . . .	131
7.1. Conclusions . . . . .	131
7.2. Future Work . . . . .	135
REFERENCES . . . . .	137
APPENDIX	
A THREE-DIMENSIONAL FINITE ELEMENT MODELING ON BOLTED PLATE	150
B PHYSICS BASED THREE-DIMENSIONAL FINITE ELEMENT MODELING OF LUG JOINT SAMPLE . . . . .	156
C LOG-NORMAL DISTRIBUTION . . . . .	160
C.1. Log-normal . . . . .	161
C.2. Discretized Log-normal . . . . .	161
D NEGATIVE-BINOMIAL DISTRIBUTION . . . . .	163
E LEARNING MULTI-DIMENSIONAL GAUSSIAN MIXTURE MODEL . . . . .	165
INDEX . . . . .	168

## LIST OF TABLES

Table	Page
3.1. MPD classification results without optimization. . . . .	46
3.2. MPD classification results with optimization. . . . .	47
3.3. Time-domain correlation based classification results for data from PZT4. . .	48
3.4. MMPD classification results for data from PZT3. . . . .	49
3.5. MPD classification results with sensor fusion. . . . .	51
3.6. MMPD classification on ultrasonic data. . . . .	56
4.1. Structural damage classification using discrete HMM ( $K_{\text{obs}} = 256$ symbols). .	68
4.2. Structural damage classification using continuous HMM. . . . .	68
4.3. Damage classification rates from HMM . . . . .	68
4.4. Material damage classification using discrete HMM ( $K_{\text{obs}} = 256$ symbols). .	69
4.5. Material damage classification using continuous HMM. . . . .	69
4.6. Material damage classification rates from HMM . . . . .	69
4.7. Confusion matrices for different SNRs (U: unfatigued, F: fatigued). . . . .	77
6.1. Summary of correct classification. . . . .	129
A.1. Material properties used for washers, plate, and nuts. . . . .	152
A.2. Modal frequencies with bolt at 100% . . . . .	153
A.3. Modal frequencies with 3 bolt at 25% . . . . .	153

## LIST OF FIGURES

Figure	Page
1.1. The linear chirp response at different PZT locations. . . . .	3
3.1. Flowchart summarizing the steps of the MPD algorithm. . . . .	25
3.2. Sample dictionary showing time-frequency shifted and scaled atoms. . . . .	28
3.3. Comparison of WD and MPD-TFR . . . . .	29
3.4. Flowchart summarizing a classification algorithm based on MPD features. . . . .	32
3.5. Flowchart summarizing a classification algorithm based on MMPD features. . . . .	35
3.6. Experimental setup for fastener damage in a square aluminum plate. . . . .	36
3.7. Example time-domain plots . . . . .	38
3.8. MPD of Class 1 signal from PZT3 . . . . .	39
3.9. Example time-frequency plots showing WD . . . . .	40
3.10. Parallelization efficiency of the MPD implementation. . . . .	41
3.11. Power spectral density . . . . .	42
3.12. Residue energy fraction versus MMPD iterations. . . . .	44
3.13. Sensor fusion approach. . . . .	50
3.14. Three-point bend fatiguing of the aluminum plates. . . . .	52
3.15. Schematic for Ultrasonic based detection. . . . .	53
3.16. Data and preprocessing. . . . .	55
3.17. TFR on Ultrasonic signals. . . . .	57
4.1. MPD-TFR of a real signal from a bolted joint, demonstrating a 3-state definition used in the HMM classifier. . . . .	62
4.2. Setup for structural and material damage in a bolted joint. . . . .	66

Figure	Page
4.3. Log-evidence as a function of number of HMM states . . . . .	67
4.4. Time domain and time-frequency domain plots of example signals from un- fatigued and fatigued data at 20 dB SNR. . . . .	72
4.5. Time domain and time-frequency domain plots of example signals from un- fatigued and fatigued data at 0 dB SNR. . . . .	73
4.6. Effect of noise on MPD residual error and TFR reconstruction (for 30 itera- tions). . . . .	74
4.7. MPD-TFR of synthesized lug joint signal at 20dB SNR, to aid in choosing number of HMM states. . . . .	76
4.8. Receiver operating characteristic (ROC) curves for different SNRs. . . . .	78
5.1. Convergence of Monte Carlo integration . . . . .	81
5.2. Demonstrating that a Markov chain converges to a stationary distribution. . . . .	84
5.3. Blocked Gibbs sampling for learning a 1-dimensional Gaussian Mixture Model using Dirichlet Process. . . . .	100
5.4. Block diagram showing progressive damage estimation using adaptive learning. . . . .	101
5.5. A comparison of non-uniform vs. uniform feature selection. . . . .	105
5.6. The compact tension (CT) sample. . . . .	115
5.7. Envelope of loading cycle for CT sample. . . . .	116
5.8. Example MPD-TFR of signals from two of the observed damage states. . . . .	116
5.9. MPD-TFRs of two signals for a crack length of 6.17 mm. . . . .	117
5.10. Adaptive learning on features showing two clusters. . . . .	118
5.11. Active data selection for improved adaptive learning. . . . .	119

Figure	Page
5.12. 1-norm of the difference ( $\mathcal{E}$ ) in true and estimated pdf. . . . .	120
5.13. Crack estimation at every damage cycle. . . . .	121
6.1. The lug sample under investigation. . . . .	126
6.2. The actuation signal. . . . .	127
6.3. MPD from sensor 1. . . . .	128
6.4. Transfer Learning for Fatigue Damage Classification . . . . .	129
6.5. Graphical representation of confusion matrix. . . . .	130
A.1. Boundary conditions and meshes for the aluminum plate. . . . .	151
A.2. Example modes under different boundary conditions. . . . .	155
B.1. Modeled lug joint sample showing sensor location, crack and dimensions. . .	157
B.2. Three-dimensional FEM with boundary condition and layers. . . . .	158
C.1. Comparing log-normal and discretized log-normal . . . . .	162

## REFERENCES

- [1] C. R. Farrar and K. Worden, “An introduction to structural health monitoring,” *Philosophical Transactions of the Royal Society A*, vol. 365, pp. 303–315, 2007.
- [2] W. J. Staszewski, C. Boller, and G. Tomlinson, *Structural Health Monitoring of Aerospace Structures, Smart Sensor Technologies and Signal Processing*. John Wiley and Sons, Ltd, 2004.
- [3] H. T. Yolken and G. A. Matzkanin, “Recent trends in structural health monitoring technologies,” *The AMMTIAC Quarterly*, vol. 3, no. 4, pp. 3–6, 2008.
- [4] C. R. Farrar and N. A. J. Lieven, “Damage prognosis: The future of structural health monitoring,” *Royal Society of London Transactions Series A*, vol. 365, pp. 623–632, 2007.
- [5] S. Doebling and C. R. Farrar, “Statistical damage identification techniques applied to the I-40 bridge over the Rio Grande,” in *International Modal Analysis Conference*, Santa Barbara, CA, 1998.
- [6] C. Farrar, D. Nix, T. Duffey, P. Cornwell, and G. Pardoën, “Damage identification with linear discriminant operators,” in *International Modal Analysis Conference*, Kissimmee, FL, 1999.
- [7] H. Sohn and C. R. Farrar, “Damage diagnosis using time series analysis of vibration signals,” *Smart Material Structures*, vol. 10, pp. 446–451, June 2001.
- [8] H. Sohn, C. R. Farrar, N. F. Hunter, and K. Worden, “Structural health monitoring using statistical pattern recognition techniques,” *Transactions of the ASME*, vol. 123, pp. 706–711, 2001.
- [9] G. Park, H. Sohn, C. R. Farrar, and D. J. Inman, “Overview of piezoelectric impedance-based health monitoring and the path forward,” *Shock and Vibration Digest*, vol. 35, no. 6, pp. 451–463, November 2003.
- [10] L. Gelman, V. Giurgiutiu, and I. Petrunin, “Advantage of using the Fourier components pair instead of power spectral density for fatigue crack diagnostics,” *International Journal of Condition Monitoring and Diagnostic Engineering Management*, vol. 7, pp. 18–22, 2004.
- [11] H. Sohn and K. H. Law, “Bayesian probabilistic damage detection of a reinforced-concrete bridge column,” *Earthquake Engineering Structural Dynamics*, vol. 29, pp. 1139–1152, 2000.

- [12] M. Nguyen, X. Wang, Z. Su, and L. Ye, "Damage identification for composite structures with a Bayesian network," in *Intelligent Sensors, Sensor Networks and Information Processing Conference*, 2004, pp. 307–311.
- [13] H. Sohn, D. W. Allen, K. Worden, and C. R. Farrar, "Structural damage classification using extreme value statistics," *Journal of Dynamic Systems, Measurement, and Control*, vol. 127, pp. 125–132, 2005.
- [14] S. Das, A. N. Srivastava, and A. Chattopadhyay, "Classification of damage signatures in composite plates using one-class SVMs," in *Aerospace Conference, 2007 IEEE*, March 2007, pp. 1–19.
- [15] W. J. Staszewski, "Structural and mechanical damage detection using wavelets," *The Shock and Vibration Digest*, vol. 30, pp. 457–472, 1998.
- [16] H. Jeong and Y. Jang, "Fracture source location in thin plates using the wavelet transform of dispersive waves," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 47, pp. 612–619, 2000.
- [17] A. Sun and C. C. Chang, "Statistical wavelet-based method for structural health monitoring," *Journal of Structural Engineering*, vol. 130, no. 7, pp. 1055–1062, July 2004.
- [18] V. Pakrashia, B. Basu, and A. O. Connora, "Structural damage detection and calibration using a wavelet-kurtosis technique," *Engineering Structures*, vol. 29, no. 9, pp. 2097–2108, September 2007.
- [19] A. Karasaridis, M. Maalej, S. Pantazopoulou, and D. Hatzinakos, "Time-frequency analysis of sensor data for detection of structural damage in instrumented structures," in *International Conference on Digital Signal Processing*, vol. 2, 1997, pp. 817–820.
- [20] M. M. R. Taha, A. Noureldin, J. L. Lucero, and T. J. Baca, "Wavelet transform for structural health monitoring: A compendium of uses and features," *Structural Health Monitoring*, vol. 5, no. 3, pp. 267–295, 2006.
- [21] D. Chakraborty, N. Kovvali, J. Wei, A. Papandreou-Suppappola, D. Cochran, and A. Chattopadhyay, "Damage Classification Structural Health Monitoring in Bolted Structures Using Time-frequency Techniques," *Journal of Intelligent Material Systems and Structures, special issue on Structural Health Monitoring*, vol. 20, no. 11, pp. 1289–1305, July 2009.
- [22] L. Channels, D. Chakraborty, B. Butrym, N. Kovvali, J. Spicer, A. Papandreou-Suppappola, M. Afshari, D. Inman, and A. Chattopadhyay, "A comparative study of

- fatigue damage sensing in aluminum alloys using electrical impedance and laser ultrasonic methods,” in *Proc. of SPIE, Smart Structures and Materials & Non-destructive Evaluation and Health Monitoring*, vol. 7295, 2009, pp. 72 950Q–1 – 10.
- [23] D. Chakraborty, W. Zhou, D. Simon, N. Kovvali, A. Papandreou-Suppappola, D. Cochran, and A. Chattopadhyay, “Time-frequency methods for structural health monitoring,” in *SenSIP workshop*, Sedona, AZ, May 2008.
- [24] D. Chakraborty, S. Soni, J. Wei, N. Kovvali, A. Papandreou-Suppappola, D. Cochran, and A. Chattopadhyay, “Physics based modeling for time-frequency damage classification,” in *Proc. of SPIE, Smart Structures and Materials & Non-destructive Evaluation and Health Monitoring*, vol. 6926, 2008, pp. 69 260M1–12.
- [25] L. Channels, D. Chakraborty, D. Simon, N. Kovvali, J. Spicer, A. Papandreou-Suppappola, D. Cochran, P. Peralta, and A. Chattopadhyay, “Ultrasonic sensing and time-frequency analysis for detecting plastic deformation in an aluminum plate,” in *Proc. of SPIE, Smart Structures and Materials & Non-destructive Evaluation and Health Monitoring*, vol. 6926, 2008, pp. 69 260P1–10.
- [26] W. Zhou, D. Chakraborty, N. Kowali, A. Papandreou-Suppappola, D. Cochran, and A. Chattopadhyay, “Damage classification for structural health monitoring using time-frequency feature extraction and continuous hidden Markov models,” in *Conference Record of the Forty-First Asilomar Conference on Signals, Systems and Computers ACSSC 2007*, November 2007, pp. 848–852.
- [27] W. Zhou, N. Kovvali, A. Papandreou-Suppappola, P. Peralta, and A. Chattopadhyay, “Progressive damage estimation using sequential Monte Carlo techniques,” in *The 7th International Workshop on Structural Health Monitoring*, Stanford, CA, 2009.
- [28] Z. Feng and F. Chu, “Nonstationary vibration signal analysis of a hydroturbine based on adaptive chirplet decomposition,” *Structural Health Monitoring*, vol. 6, no. 4, pp. 265–279, 2007. [Online]. Available: <http://shm.sagepub.com/cgi/content/abstract/6/4/265>
- [29] J. Michaels and T. Michaels, “Detection of structural damage from the local temporal coherence of diffuse ultrasonic signals,” *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control*, vol. 52, no. 10, pp. 1769–1782, October 2005.
- [30] L. Yu and V. Giurgiutiu, “Advanced signal processing for enhanced damage detection with piezoelectric wafer active sensors,” *Smart Structures and Systems*, vol. 1, no. 2, pp. 185–215, 2005.

- [31] B. Liu, S. Ling, and R. Gribonval, "Bearing failure detection using matching pursuit," *NDTE International*, vol. 35, pp. 255–262, 2002.
- [32] V. Giurgiutiu, J. Bao, and W. Zhao, "Active sensor wave propagation health monitoring of beam and plate structures," in *SPIE International Symposium on Smart Structures and Materials*, March 2001, pp. 1–12.
- [33] V. Giurgiutiu and A. Zagra, "Damage detection in thin plates and aerospace structures with the electro-mechanical impedance method," *Structural Health Monitoring*, vol. 4, no. 2, pp. 99–118, 2005.
- [34] A. Graps, "An introduction to wavelets," *Computational Science & Engineering, IEEE*, vol. 2, no. 2, pp. 50 – 61, 1995.
- [35] L. Eren and M. J. Devaney, "Bearing damage detection via wavelet packet decomposition of the stator current," *IEEE Transactions on Instrumentation and Measurement*, vol. 53, pp. 431–436, 2004.
- [36] C. A. Paget, S. Grondel, K. Levin, and C. Delebarre, "Damage assessment in composites by Lamb waves and wavelet coefficients," *Smart Materials and Structures*, vol. 12, no. 3, pp. 393–402, 2003.
- [37] U. Junga and B.-H. Koh, "Structural damage localization using wavelet-based silhouette statistics," *Journal of Sound and Vibration*, vol. 321, pp. 590–604, 2009.
- [38] Z. Hou, M. Noori, and R. S. Amand, "Wavelet-based approach for structural damage detection," *Journal of Engineering Mechanics*, vol. 12, no. 7, pp. 677–683, 2000.
- [39] A. Nuruzzaman, O. Boyraz, and B. Jalali, "Time-stretched short-time Fourier transform," *IEEE Transactions on Instrumentation and Measurement*, vol. 55, no. 2, pp. 598 – 602, 2006.
- [40] R. A. Altes, "Detection, estimation and classification with spectrograms," *The Journal of the Acoustic Society of America*, vol. 67, no. 4, pp. 1232–1246, April 1980.
- [41] L. Cohen, "Time-frequency distribution - A review," *IEEE proceedings*, vol. 77, no. 7, pp. 941–981, July 1989.
- [42] S. G. Mallat and Z. Zhang, "Matching pursuits with time-frequency dictionaries," *IEEE Trans. on Signal Processing*, vol. 41, pp. 3397–3415, December 1993.

- [43] P. Seung-Hee, Y. Chung-Bang, and R. Yongrae, "PZT-induced lamb waves and pattern recognitions for on-line health monitoring of jointed steel plates," in *Sensors and smart structures technologies for civil, mechanical, and aerospace systems* :, vol. 5765. San Diego, CA: International Society of Photo-Optical Instrumentation Engineers, Bellingham, WA, March 2005.
- [44] S. E. Olson, M. P. DeSimio, and M. M. Derriso, "Fastener damage estimation in a square aluminum plate," *Structural Health Monitoring*, vol. 5, pp. 173–183, 2006.
- [45] N. Kovvali, S. Das, D. Chakraborty, D. Cochran, A. Papandreou-Suppapola, and A. Chattopadhyay, "Time-frequency based classification of structural damage," in *48th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, Honolulu, Hawaii, April 2007, pp. 2047–2055.
- [46] D. Chakraborty, N. Kovvali, J. Zhang, A. Papandreou-Suppappola, and A. Chattopadhyay, "Adaptive learning for damage classification in structural health monitoring," in *43rd Asilomar Conference on Signals, Systems and Computers*, Pacific Grove, California, November 2009.
- [47] T. S. Ferguson, "A Bayesian analysis of some nonparametric problems," *The Annals of Statistics*, vol. 1, pp. 209–230, 1973.
- [48] C. E. Antoniak, "Mixtures of Dirichlet processes with applications to Bayesian nonparametric problems," *The Annals of Statistics*, vol. 2, pp. 1152–1174, 1974.
- [49] M. D. Escobar and M. West, "Bayesian density estimation and inference using mixtures," *Journal of the American Statistical Association*, vol. 90, pp. 577–588, 1995.
- [50] C. E. Rasmussen, "The infinite Gaussian mixture model," in *Advances in Neural Information Processing Systems 12*, S. A. Solla, T. K. Leen, and K.-R. Muller, Eds. MIT Press, 2000, pp. 554–560.
- [51] A. Ranganathan, "The Dirichlet process mixture (dpm) model," September 2004. [Online]. Available: [http://biocomp.bioen.uiuc.edu/journal\\_club\\_web/dirichlet.pdf](http://biocomp.bioen.uiuc.edu/journal_club_web/dirichlet.pdf)
- [52] D. M. Blei and M. I. Jordan, "Variational inference for Dirichlet process mixtures," *Bayesian Analysis*, vol. 1, no. 1, pp. 121–144, 2006.
- [53] P. Fearnhead, "Particle filters for mixture models with an unknown number of components," *Journal of Statistics and Computing*, vol. 14, pp. 11–21, 2004. [Online]. Available: [citeseer.ist.psu.edu/754210.html](http://citeseer.ist.psu.edu/754210.html)

- [54] Y. Qi, J. Paisley, and L. Carin, "Music analysis using hidden Markov mixture models," *IEEE Transactions on Signal Processing*, vol. 55, no. 11, pp. 5209–5224, 2007.
- [55] X. Wang, X. Ma, and W. E. L. Grimson, "Unsupervised activity perception in crowded and complicated scenes using hierarchical Bayesian models," *IEEE Transactions on Pattern Analysis & Machine Intelligence*, vol. 31, no. 3, pp. 539–555, Mar. 2009.
- [56] E. Ozkan, I. Y. Ozbek, and M. Demirekler, "Dynamic speech spectrum representation and tracking variable number of vocal tract resonance frequencies with time-varying Dirichlet process mixture models," *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 17, no. 8, pp. 1518–1532, Nov. 2009.
- [57] F. Caron, M. Davy, A. Doucet, E. Duflos, and P. Vanheeghe, "Bayesian inference for linear dynamic models with Dirichlet process mixtures," *IEEE Transaction on Signal Processing*, vol. 56, no. 1, pp. 71–84, Jan. 2008.
- [58] I. Pruteanu-Malinici and L. Carin, "Infinite hidden Markov models for unusual-event detection in video," *IEEE Transactions on Image Processing*, vol. 17, no. 5, pp. 811–822, May 2008.
- [59] W. Hastings, "Monte Carlo sampling methods using Markov chains and their applications," *Biometrika*, vol. 57, no. 1, pp. 97–109, 1970.
- [60] N. Metropolis, A. Rosenbluth, M. N. Rosenbluth, A. Teller, and H. Teller, "Equations of state calculations by fast computing machines," *Journal of Chemical Physics*, vol. 21, pp. 1087–1091, 1953.
- [61] N. Metropolis and S. Ulam, "The Monte Carlo method," *Journal of the American Statistical Association*, vol. 44, no. 247, pp. 335–341, September 1949.
- [62] S. Pan and Q. Yang, "A survey on transfer learning," *Knowledge and Data Engineering, IEEE Transactions on*, pp. 1 – 15, 2009, pre-published version.
- [63] S. Thrun, "Is learning the n-th thing any easier than learning the first?" in *Advances in Neural Information Processing Systems*. The MIT Press, 1996, pp. 640–646.
- [64] R. Caruana, "Multitask learning," *Mach. Learn.*, vol. 28, no. 1, pp. 41–75, 1997.
- [65] S. Thrun and L. Y. Pratt, Eds., *Learning to learn*. Kluwer Academic Publishers, 1998.

- [66] J. Baxter, “A model of inductive bias learning,” *Journal of Artificial Intelligence Research*, vol. 12, pp. 149–198, 2000.
- [67] R. Raina, A. Battle, H. Lee, B. Packer, and A. Y. Ng, “Self-taught learning: Transfer learning from unlabeled data,” in *Proceedings of the 24th international conference on Machine learning*, 2007.
- [68] W. Dai, Y. Chen, G.-R. Xue, Q. Yang, and Y. Yu, “Translated learning: Transfer learning across different feature spaces,” in *Proceedings of the 22nd Annual Conference on Neural Information Processing Systems (NIPS-08)*, Vancouver, Canada, 2008.
- [69] A. Arnold, R. Nallapati, and W. W. Cohen, “A comparative study of methods for transductive transfer learning,” in *7th IEEE International Conference on Data Mining Workshops*, IEEE Computer Society, Washington, DC, USA, 2007, pp. 77 – 82.
- [70] G. Hinton and T. J. Sejnowski, Eds., *Unsupervised Learning: Foundations of Neural Computation*. MIT Press, 1999.
- [71] D. G. S. Richard O. Duda, Peter E. Hart, *Pattern classification*, 2nd ed. New York: Wiley, 2001, ch. Unsupervised Learning and Clustering, p. 571.
- [72] S. Kotsiantis and P. Pintelas, “Recent advances in clustering: A brief survey,” *WSEAS Transactions on Information Science and Applications*, vol. 1, no. 1, pp. 73–81, 2004.
- [73] S. W. Doebling, C. R. Farrar, M. B. Prime, and D. W. Shevitz, “Damage identification and health monitoring of structural and mechanical systems from changes in their vibration characteristics: A literature review,” Los Alamos National Laboratory, New Mexico, Tech. Rep. LA-13070-MS, 1996.
- [74] H. Sohn, C. R. Farrar, F. M. Hemez, D. D. Shunk, D. W. Stinemat, and B. R. Nadler, “A review of structural health monitoring literature: 1996 – 2001,” Los Alamos National Laboratory, Tech. Rep. LA-13976-MS, 2003.
- [75] H. Sohn and C. R. Farrar, “Time series analyses for locating damage sources in vibration systems,” in *International Conference on Noise and Vibration Engineering*, Leuven, Belgium, September 2000.
- [76] D. George, N. Hunter, C. Farrar, and R. Deen, “Identifying damage sensitive features using nonlinear time-series and bispectral analysis,” in *IMAC 18*, San Antonio, Texas, February 2000.

- [77] V. Giurgiutiu and J. Bao, "Embedded-ultrasonics structural radar for *In Situ* structural health monitoring of thin-wall structures," *Structural Health Monitoring*, vol. 3, no. 2, pp. 121–140, 2004.
- [78] O. Balogun, G. Cole, R. Huber, D. Chinn, T. Murray, and J. Spicer., "High spatial resolution sub-surface acoustic microscopy in mesoscale structures using a laser-based ultrasonic technique," *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control*, 2008.
- [79] O. Balogun, R. Huber, D. Chinn, and J. Spicer, "Laser ultrasonic inspection of the microstructural state of thin metal foils," *Journal of the Acoustical Society of America*, vol. 125, no. 3, pp. 1437–1443, 2009.
- [80] V. Rao, "Kurtosis as a metric in the assessment of gear damage," *The Shock and Vibration Digest*, vol. 31, no. 6, pp. 443–448, 1999.
- [81] L. J. Hadjileontiadisa and E. Doukab, "Kurtosis analysis for crack detection in thin isotropic rectangular plates," *Engineering Structures*, vol. 29, no. 9, pp. 2353–2364, September 2007.
- [82] B. P. Bogert, M. J. R. Healy, and J. W. Tukey, *The Quefrequency Analysis of Time Series for Echoes: Cepstrum, Pseudo Autocovariance, Cross-Cepstrum and Saphe Cracking*. New York: Wiley, 1963, ch. 15, pp. 209–243.
- [83] J. G. Proakis and D. K. Manolakis, *Digital Signal Processing*, 4th ed. Prentice Hall, 2004.
- [84] A. Morassi and F. Vestroni, Eds., *Dynamic Methods for Damage Detection in Structures*, 1st ed. Springer, 2009.
- [85] S. Mallat, *A Wavelet Tour of Signal Processing*, 2nd ed. Academic Press, 1998.
- [86] L. Cohen, *Time Frequency Analysis: Theory and Applications*. Prentice Hall, 1994.
- [87] F. Hlawatsch and G. F. Boudreaux-Bartels, "Linear and quadratic time-frequency signal representations," *IEEE Signal Processing Magazine*, vol. 9, no. 2, pp. 21–67, April 1992.
- [88] A. Papandreou-Suppappola, Ed., *Applications in Time-Frequency Signal Processing*. Florida: CRC Press, 2002.

- [89] A. Papandreou-Suppappola and S. B. Suppappola, "Analysis and classification of time-varying signals with multiple time-frequency structures," *IEEE Signal Processing Letters*, vol. 9, pp. 92–95, 2002.
- [90] S. P. Ebenezer, A. Papandreou-Suppappola, and S. B. Suppappola, "Classification of acoustic emissions using modified matching pursuit," *EURASIP Journal on Applied Signal Processing*, vol. 3, pp. 347–357, 2004.
- [91] L. Channels, D. Chakraborty, D. Simon, N. Kovvali, J. Spicer, A. Papandreou-Suppappola, D. Cochran, P. Peralta, and A. Chattopadhyay, "Ultrasonic sensing and time-frequency analysis for detecting plastic deformation in an aluminum plate," in *International Symposium on Smart structures and Materials & Nondestructive Evaluation and Health Monitoring*, vol. 6926, 2008.
- [92] D. Chakraborty, S. Soni, J. Wei, N. Kovvali, A. Papandreou-Suppappola, D. Cochran, and A. Chattopadhyay, "Physics based modeling for time-frequency damage classification," in *International Symposium on Smart structures and Materials & Nondestructive Evaluation and Health Monitoring*, vol. 6926, 2008.
- [93] L. R. F. Rose, "Point-source representation for laser-generated ultrasound," *Journal of the Acoustical Society of America*, vol. 75, pp. 723–732, 1984.
- [94] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," in *Proceedings of the IEEE*, vol. 77, 1989, pp. 257–286.
- [95] A. Dempster, N. Laird, and D. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," *Journal of the Royal Statistical Society, Series B*, vol. 39, pp. 1–38, 1977.
- [96] D. J. C. MacKay, *Information Theory, Inference, and Learning Algorithms*. Cambridge University Press, 2003.
- [97] M. J. Beal, "Variational algorithms for approximate Bayesian inference," Ph.D. dissertation, Gatsby Computational Neuroscience Unit, University College London, 2003.
- [98] D. J. C. MacKay, "Ensemble learning for hidden Markov models," Cavendish Laboratory, University of Cambridge, Tech. Rep., 1997.
- [99] S. Ji, B. Krishnapuram, and L. Carin, "Variational Bayes for continuous hidden Markov models and its application to active learning," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, pp. 522–532, 2006.

- [100] S. G. Mallat and Z. Zhang, “Matching pursuits with time-frequency dictionaries,” *IEEE Transactions on Signal Processing*, vol. 41, pp. 3397–3415, 1993.
- [101] S. Weinzierl, “Introduction to monte carlo methods,” 2000. [Online]. Available: <http://www.citebase.org/abstract?id=oai:arXiv.org:hep-ph/0006269>
- [102] W. Gilks, S. Richardson, and D. Spiegelhalter, *Markov Chain Monte Carlo in Practice*. Chapman & Hall/CRC, 1996.
- [103] A. F. M. Smith, “Bayesian computational methods,” *Philosophical Transactions: Physical Sciences and Engineering*, vol. 337, no. 1647, pp. 369–386, 1991. [Online]. Available: <http://www.jstor.org/stable/53988>
- [104] M. Evans and T. Swartz, “Methods for approximating integrals in statistics with special emphasis on Bayesian integration problems,” *Statistical Science*, vol. 10, no. 3, pp. 254–272, 1995.
- [105] M. A. Tanner, *Tools for Statistical Inference: Methods for the Exploration of Posterior Distributions and Likelihood Functions*, 3rd ed., ser. Springer Series in Statistics. Springer, 1996.
- [106] M. K. Cowles and B. P. Carlin, “Markov Chain Monte Carlo Convergence Diagnostics: A Comparative Review,” *Journal of the American Statistical Association*, vol. 91, no. 434, pp. 883–904, Jun 1996.
- [107] A. E. Raftery and S. Lewis, “How many iterations in the gibbs sampler,” in *In Bayesian Statistics 4*, vol. 4, 1992, pp. 763–773. [Online]. Available: <http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.41.6474>
- [108] A. E. Raftery and S. M. Lewis, “Comment: One long run with diagnostics: Implementation strategies for Markov chain Monte Carlo,” *Statistical Science*, vol. 7, no. 4, pp. 493 – 497, November 1992.
- [109] A. Gelman and D. B. Rubin, “A single series from the Gibbs sampler provides a false sense of security,” *Bayesian Statistics*, vol. 4, pp. 625 – 631, 1992.
- [110] ———, “Inference from iterative simulation using multiple sequences,” *Statistical Science*, vol. 7, no. 4, pp. 457 – 511, 1992.
- [111] G. Casella and E. I. George, “Explaining the Gibbs sampler,” *The American Statistician*, vol. 46, no. 3, pp. 167 – 174, August 1992.

- [112] A. E. Gelfand and A. F. M. Smith, “Sampling-based approaches to calculating marginal densities,” *Journal of the American Statistical Association*, vol. 85, no. 410, pp. 398 – 409, June 1990.
- [113] A. Gelman, J. B. Carlin, H. S. Stern, and D. B. Rubin, *Bayesian Data Analysis*, 2nd ed. CRC Press, 2004.
- [114] Y. W. Teh, “Dirichlet processes,” 2007, submitted to Encyclopedia of Machine Learning. [Online]. Available: [www.gatsby.ucl.ac.uk/~ywteh/research/npbayes/dp.pdf](http://www.gatsby.ucl.ac.uk/~ywteh/research/npbayes/dp.pdf)
- [115] H. Ishwaran and L. F. James, “Gibbs sampling methods for stick-breaking priors,” *Journal of the American Statistical Association*, vol. 96, pp. 161–173, 2001.
- [116] J. Sethuraman, “A constructive definition of Dirichlet priors,” *Statistica Sinica*, vol. 4, pp. 639–650, 1994.
- [117] D. Blackwell and J. B. MacQueen, “Ferguson distributions via Polyá urn schemes,” *The Annals of Statistics*, vol. 1, pp. 353–355, 1973.
- [118] K. Ni, Y. Qi, and L. Carin, “Multi-aspect target classification and detection via the infinite hidden Markov model,” in *IEEE International Conference on Acoustics, Speech and Signal Processing*, vol. 2, 2007, pp. II–433–II–436.
- [119] Y. Qi, J. W. Paisley, and L. Carin, “Dirichlet process HMM mixture models with application to music analysis,” in *IEEE International Conference on Acoustics, Speech and Signal Processing*, vol. 2, 2007, pp. II–465–II–468.
- [120] M. West, P. Muller, and M. D. Escobar, “Hierarchical priors and mixture models, with applications in regression and density estimation,” in *Aspects of Uncertainty*, P. R. Freeman and A. F. Smith, Eds. John Wiley, 1994, pp. 363–386.
- [121] R. M. Neal, “Markov chain sampling methods for Dirichlet process mixture models,” *Journal of Computational and Graphical Statistics*, vol. 9, pp. 249–265, 2000.
- [122] S. Kullback and R. Leibler, “On information and sufficiency,” *The Annals of Mathematical Statistics*, vol. 22, no. 1, pp. 79–86, 1951.
- [123] S. Kullback, “The Kullback-Leibler distance,” *The American Statistician*, vol. 41, pp. 340–341, 1987.

- [124] A. Bhattacharyya, “On a measure of divergence between two statistical populations defined by their probability distributions,” *Bulletin of the Calcutta Mathematical Society*, vol. 35, pp. 99–109, 1943, mR0010358.
- [125] T. Kailath, “The divergence and Bhattacharyya distance measures in signal selection,” *IEEE Transactions on Communication Technology*, vol. 15, no. 1, pp. 52–60, 1967.
- [126] G. L. Yang, L. Cam, and L. M., *Asymptotics in Statistics: Some Basic Concepts*. Berlin: Springer., 2000, iISBN 0-387-95036-2.
- [127] D. Chakraborty, N. Kovvali, A. Papandreou-Suppappola, and A. Chattopadhyay, “Active learning data selection for adaptive online structural damage estimation,” in *Proc. of SPIE, Smart Structures and Materials & Non-destructive Evaluation and Health Monitoring*, 2010.
- [128] L. Kuipers and H. Niederreiter, *Uniform Distribution of Sequences*, L. Bers, P. Hilton, and H. Hochstadt, Eds. John Wiley & Sons Inc., 1974.
- [129] B. Chazelle, *The Discrepancy Method*. Cambridge University Press, 2002.
- [130] S. Boyd and L. Vandenberghe, *Convex Optimization*. New York, NY: Cambridge University Press, 2004.
- [131] H. Niederreiter, “Discrepancy and convex programming,” *Annali di Matematica Pura ed Applicata*, vol. 93, pp. 89–97, 1972.
- [132] D. P. Dobkin and D. Eppstein, “Computing the discrepancy,” in *Proceedings of the ninth Annual Symposium on Computational Geometry*, 1993, pp. 47–52.
- [133] D. P. Dobkin, D. Eppstein, and D. P. Mitchell, “Computing the discrepancy with applications to supersampling patterns,” *ACM Transactions on Graphics (TOG)*, vol. 15, pp. 354–376, 1996.
- [134] S. Haykin, *Neural Networks and Learning Machines*, 3rd ed. Pearson Education Inc., 2009.
- [135] S. Mohanty, R. Teale, A. Chattopadhyay, P. Peralta, and C. Willhauck, “Mixed Gaussian process and state-space approach for fatigue crack growth prediction,” in *Structural Health Monitoring*, F.-K. Chang, Ed. PA, USA: DEStech Publications, Inc., 2007.

- [136] A. Ray and R. Patankar, "Fatigue crack growth under variable-amplitude loading: Part I – Model formulation in state-space setting," *Applied Mathematical Modelling*, vol. 25, no. 11, pp. 979–994, November 2001.
- [137] ———, "Fatigue crack growth under variable-amplitude loading: Part II - Code development and model validation," *Applied Mathematical Modelling*, vol. 25, no. 11, pp. 995–1013, November 2001.
- [138] J. N. Yang and S. D. Manning, "A simple second order approximation for stochastic crack growth analysis," *Engineering Fracture Mechanics*, vol. 53, no. 5, pp. 677–686, March 1996.
- [139] S. Mohanty, R. Teale, A. Chattopadhyay, P. Peralta, and C. Willhauck, "Mixed Gaussian process and state-space approach for fatigue crack growth prediction," in *International Workshop on Structural Health Monitoring*, vol. 2, 2007, pp. 1108–1115.
- [140] *ABAQUS*, 2007, version 6.7.1.
- [141] J. L. Rose, Ed., *Ultrasonic Waves in Solid Media*. Cambridge: University Press, Cambridge, 1999.
- [142] M. Abramowitz and I. Stegun, *Handbook of Mathematical Functions*. [Online]. Available: <http://www.math.hkbu.edu.hk/support/aands/toc.htm>
- [143] F. Dominici, G. Parmigiani, and M. Clyde, "Conjugate analysis of multivariate normal data with incomplete observations," *The Canadian Journal of Statistics*, vol. 28, no. 3, pp. 533–550, September 2000.
- [144] J. Paisley and L. Carin, "Hidden Markov models with stick-breaking priors," *IEEE Transactions on Signal Processing*, vol. 57, no. 10, pp. 3905–3917, 2009.
- [145] D. Fink, "A compendium of conjugate priors," Montana State Univeristy, Tech. Rep., 1995.

## INDEX

- k*-means, 66
- acoustic emission, 17
- active data selection, 101
- adaptive learning
  - definition, 79
- adjoint, 82
- almost surely discrete, 88
- aluminum
  - 2024-T351 plates, 51
  - 6061-T6 plates, 51
- aluminum 2024 T3, 115
- aluminum plate, 35
- atoms, 23, 24, 39
  - Gaussian, 25
- base distribution, 88
- basis, 25
- Baum-Welch algorithm, 59
- Bayes' theorem, 110
- Bayesian decision fusion, 5
- Bayesian filter, 109
- Bayesian filtering, 6
- Bayesian sensor fusion, 125
- burn-in, 83
- C, 39
- cepstrum, 19
- class memberships, 122
- classification, 29, 37
  - 2-D, 5
- classification performance, 41
- classifier
  - optimize, 41
- clustering, 96
- clusters, 94
- compact tension, 115
- confusion matrix, 10, 77
- converge, 23
- correlation, 21, 26
  - 2-D, 30
- crest factor, 18
- cross-terms, 27
- cross-validation, 43
- damage, 29
  - class, 29
  - surface, 52
- damage quantification, 1
- data fusion
  - Bayesian, 49
- detection, 1
- dictionary, 23, 24, 31, 39
  - complete, 24
  - MMPD, 43
- Dirichlet
  - process, 8, 87
  - process marginal distribution, 88
  - process mixture model, 8
- Dirichlet process, 6
  - mixture model, 6
  - posterior, 90
- Dirichlet process mixture model
  - infinite, 90
- discrete
  - state, 83
- distribution
  - candidate generating, 85
  - proposal, 85
  - Dirichlet, 167
  - Normal-Wishart, 166
  - Wishart, 166
- distribution over distributions, 88
- DP prior, 96
- eigenfunction, 82
- eigenvalue, 82
- electromagnetic impedance, 20
- ensemble, 61
- ensemble learning, 64
- expectation, 80, 81
- expectation operator, 80
- expectation-maximization, 8, 59, 86
- expected distribution, 88
- false alarm, 77
- fatigue, 70
- feature extraction, 37
- feature reduction, 104
- finite element analysis, 8, 42
- finite element model, 8
- finite element modeling, 70

- first-in-first-out, 101
- Fourier transform, 8, 19, 20
  - short time, 20
  - fast, 26
  - short time, 54
  - short-time, 9
- frequency shift, 25
- Gaussian
  - 2-D, 31
  - atom, 5
  - function, 27
  - functions, 28
  - Wigner Distribution, 27
- Gaussian distribution, 58
- Gaussian function, 28
- Gaussian mixture model, 8, 58, 96
- Gaussian noise, 70
- Gibbs sampler
  - blocked, 94, 98
- Gibbs sampling, 92
- hidden Markov model, 8, 58, 61, 127
  - continuous, 58
  - discrete, 58
- hierarchical Bayesian model, 90
- hyper-parameters, 98
- impedance signal, 20
- in situ, 1
- initial state distribution, 82
- initial state distribution vector, 58
- innovation parameter, 88
- Instron 1331, 115
- interferometer
  - Michelson-type, 52
- Kullback-Leibler distance, 9, 61
- kurtosis, 18, 21
- laser
  - Nd:YAG, 52
- laser-ultrasonic, 51
- Lead Zirconate Titanate, 20
- learning, 1
- linear frequency-modulated, 9, 36
- log-normal, 111
  - discrete, 111
- Markov chain, 82, 96
  - convergence, 82, 83
  - Monte Carlo, 9, 81
- Markov property, 82
- matching pursuit decomposition, 5, 9, 23, 28, 29, 100
- maximum a posteriori, 9, 60
- maximum-likelihood, 9
  - estimate, 59
  - learning, 59, 86
- maximum-likelihood estimate, 122
- MCMC, 6
- methods
  - active sensor wave propagation, 2
  - advanced signal processing, 1
  - Bayesian, 1
  - extreme value statistics, 1
  - Fourier component pair analysis, 1
  - impedance-based, 1
  - quadratic TFR, 4
  - statistical, 1
  - statistical pattern recognition, 1
  - STFT, 4
  - support vector machines, 1
  - time-series analysis, 1
  - vibration analysis, 2
  - wavelet transform, 4
- mixture modeling, 87
- MMPD, 43
- model
  - parametric, 122
- modified matching pursuit decomposition, 5, 9
- Monte Carlo
  - integration, 81
- MPD
  - algorithm, 23
  - expansion coefficient, 24
  - residue, 23
  - classification, 31
  - classifier, 29
  - modified, 31
- MPD expansion coefficient, 23
- MPD-PDF, 9, 100

- MPD-TFR, 9, 27–29
- noise performance, 70
- non-destructive evaluation, 1
- non-parametric, 89
- nonparametric Bayesian, 87
- Occam’s razor, 60
- orthonormal, 24
- over-fitting, 59, 71, 87
- Pólya Urn Gibbs sampling, 93
- Pólya Urn property, 88
- parameter(s), 87
- parametric Bayesian, 87
- parametric models, 87
- periodicity, 19
- piezoelectric transducer, 9, 20
- power spectral density, 9, 41
- predictive likelihood, 59
- preprocessing, 37
- probability density function, 9
- projection, 23
- pulse-echo, 18
- PZT, 35
- receiver operating characteristic, 9
- residual life estimation, 1
- residue, 23
- ROC curve, 77
- sampler
  - Gibbs, 84–86
  - Metropolis, 85
  - Metropolis-Hastings, 84–86
- sampling, 81
- scanning electron microscopy, 117
- sensor fusion, 49
- signal-to-noise ratio, 9, 53
- signal-to-noise-ratio, 70
- source
  - domain, 122
  - task, 122
- source domain, 127
- spectrogram, 70
- spectrum, 19
  - time-varying, 26
- state
  - transition matrix, 83
- state transition operator, 82
- state-dependent observation density, 58
- state-transition matrix, 58
- statistical measure of similarity, 100
- stick breaking construction, 89
- stochastic
  - matrix, 83
  - process, 87
- structural damage, 1
- structural health monitoring, 9, 29
- target
  - data, 122
  - task, 122
- template, 45
- template TFR, 30
- test, 30
- time scale, 25
- time series, 17
- time shift, 25
- time-frequency, 5, 9
  - plane, 5, 25
  - representation, 5
  - decomposition, 21
  - feature, 29
  - plane, 26, 54
  - representation, 9, 54
  - resolution, 26
- trained, 70
- training, 30, 31, 122
- training/testing paradigm, 2
- transducer
  - capacitance, 18
  - electrodynamic, 18
  - laser, 18
  - piezoelectric, 18
  - ultrasound, 18
- transfer learning, 6, 122
  - definition, 122
  - inductive, 7
    - multi-task, 7
    - self taught, 7
    - translated learning, 7
  - transductive, 7

- unsupervised, 7
- translated learning, 7
  
- ultrasonic
  - amplitude, 52
  - wave, 52
- under-fitting, 87
  
- variability
  - material, 2
  - operating conditions, 2
  - temperature, 2
- variational
  - objective function, 61
  - posterior, 61, 64
- variational Bayes, 10
  - expectation-maximization, 10
- variational Bayesian
  - expectation-maximization, 61
  - learning, 60
- variational posterior
  - optimized, 63
- vibration
  - antisymmetric, 19
  - symmetric, 19
  
- wave
  - bulk, 19
  - guided, 19
  - Lamb, 19
- wavelet decomposition, 21
- wavelet function, 21
- wavelet transform, 21
  - discrete, 21
- waves
  - axial, 4
  - flexure, 4
  - Lamb, 4
  - Raleigh, 4
  - shear, 4
- Wigner Distribution, 26
  - properties, 27
- Wigner distribution, 9
- window, 26