

Epilog – Achievements, Open Problems and New Challenges in EFS

This book deals with many aspects in the field of evolving fuzzy systems which have emerged rapidly during the last decade and meanwhile have become well established in the fuzzy community. The establishment is underlined by a huge amount of publications in international fuzzy conferences and journals (such as Fuzzy Sets and Systems (Elsevier), IEEE Transactions on Fuzzy Systems (IEEE Press), IEEE Transactions on Systems, Man and Cybernetics part B (IEEE Press), Information Sciences (Elsevier), International Journal of Approximate Reasoning (Elsevier), Applied Soft Computing (Elsevier), Evolving Systems (Springer) and others) and by the organization of several special sessions and workshops during the recent years at international fuzzy conferences and symposia. This book covers not only a comprehensive survey of the most important evolving modelling approaches and the most important incremental learning algorithms they contain, but also presenting significant extensions for guiding evolving fuzzy systems to higher process safety, predictive quality, user-friendliness and interpretability as well as understandability of its components and finally the processes which they are modelling. Applications from different industrial fields including multi-channel measurement systems (identification, prediction and plausibility analysis), visual and audio inspection tasks, psychological aspects in texture analysis, applications in bio-informatics, eSensors or financial market forecasting should underline the necessity, applicability and reliability of evolving fuzzy systems in these fields. Therefore, and as the evolving concepts presented in this book allow the machines to permanently learn from changing environments and enrich their knowledge, the book may serve as another cornerstone for a step towards computational intelligence. Even though, based on all these facets, the reader may get a nice impression about the range of applicability and the methodological richness of evolving fuzzy systems, there are still some open

problems in EFS which have not been handled with sufficient care and necessary detail so far (although discussed in some sections in this book):¹

- **Avoidance of over-fitting:** currently most of the evolving fuzzy system approaches use the least squares error optimization problem for optimizing linear parameters (mostly in rule consequent functions of TS-type fuzzy systems): this leads to a recursive least squares (in case of global learning) or recursive fuzzily weighted least squares (in case of local learning) algorithms, which may overfit significantly on the (permanently loaded) training data. This is because, the model complexity is not included in the formulation of the optimization problem; contrary in an off-line setting, the learning based on least squares error often is performed through N-fold cross-validation which can resolve the problem of over-fitting by eliciting error on separate test samples (folds) — see also Section 2.8 for a more extensive discussion on this topic. In fact, an appropriate rule merging approach as discussed in Section 5.1 may overcome some deficiencies in this regard, however this denotes a more heuristic approach rather than relying on analytical incremental optimization procedures with a more theoretic basis.
- **Fault handling:** although there exist some concepts (rule base procrastination, incremental quantiles [428], recursive potentials) for dealing with (unique, couple of) outliers in various EFS approaches, currently, there exists no enhanced concept for dealing with systematic faults, appearing in new regions of the feature space; in fact, the distinction to the appearance of new system states or operating conditions also extending the feature space has not been studied so far.
- **Drift handling:** although we presented a concept for the automatic detection and treatment of drifts and shifts in data streams in Section 4.2, this is only a first attempt in this direction, especially designed for *FLEXFIS* and *eTS* and this in a quite heuristic fashion, and therefore far from being fully investigated. In this regard, also the concept of multi-task learning [68] in connection with EFS has not been studied so far.
- **On-line curse of dimensionality reduction:** Section 5.2 indeed demonstrates a reasonable concept for a soft dimension reduction in in EFS by using feature weights whose values are changed slightly with new incoming samples, therefore discontinuities in the learning process (as would be forced by crisp on-line feature selection) can be avoided. However, this approach is far from being optimal, as the feature weighting is performed by a linear filter approach and as such not related/embedded with the underlying fuzzy model architecture. Indeed, important features in a linear sense are also important ones for non-linear fuzzy models, but some other unimportant features may turn out to be important when

¹ At this point, the author wants to emphasize that this book covers all approaches, methods and algorithms which were published before 30th of June 2010 as crisp deadline; the author apologizes for eventually overlooking some important novel concepts and aspects which were published before this date and also for not being able (due to time restrictions) to take into account any novel concepts and aspects published after this date — in both cases the author of this book would be grateful and invites the reader for any valuable comments, critics, claims, suggestions for improvement.

inspected through a non-linear approach (ideally coupled with the fuzzy model architecture as embedded approach).

- **Extrapolation problematic:** it is not fully understood how the left and right most fuzzy sets in fuzzy partitions should be optimally extended in the extrapolation region in order to give reliable predictions and classification statements; first attempts are presented in Section 4.6, especially dealing with the avoidance of re-activating inner membership functions with infinite support.

New challenges for EFS include the following aspects:

- **Active learning scenarios:** So far, the assumption in most of the EFS approaches is that the response data (labels, target values) are provided together with the input feature/variable vectors and incremental training and evolution of the models continues in a life-long learning mode. However, the concept of active learning in connection with EFS has not been sufficiently studied so far (a first attempt is presented in Section 5.3): active learning may be very important in order to decrease the annotation effort and response times of operators during on-line mode, especially for classification problems, as active learning makes explicit selection of important samples possible which may help the models to improve their qualities, and synchronously neglecting unimportant samples. This makes the application of evolving models and especially evolving fuzzy systems much more attractive.
- **Linguistic and visual interpretability:** A large part of Chapter 6 deals with aspects of complexity reduction in EFS, which can be performed in a fast on-line matter; this is far from providing interpretable and for operators, users, experts understandable EFS, only some first ideas in this direction are provided in Chapter 6. Basically, we can say that all the current EFS approaches are precise modelling approaches neglecting completely the interpretable aspect of fuzzy systems, even though including some aspects regarding deletion of obsolete rules or rule merging processes. An exception is a recent publication [180], where more interpretability is achieved by applying a kind of mixed Mamdani and Takagi-Sugeno type model architecture in order to gain more interpretability while still preserving the good approximation accuracy of TS fuzzy models. Visualization aspects and visual interpretation of (high-dimensional) EFS are completely missing in literature, but could be very important for the operators to get a better understanding of what is going on in the on-line processes of the their systems, respectively motivating the users for an enriched human-machine interaction and communication, see subsequent point.
- **Enhanced human-machine interaction:** Combining aspects of active learning with EFS and interpretable and understandable EFS together in an enriched user-interaction concepts, can be one of the key aspects in the near future such that the models benefit from both parties, data samples on the one hand and expert knowledge on the other hand in an alternating exchanging context, leading to the concept of *human-inspired evolving machine/models/fuzzy systems* (see also Section 10.2.3).

- **Dynamic data mining:** the application of EFS approaches was so far mainly concentrated on temporally changing environments. Evolving fuzzy systems have not as yet been applied in a dynamic data mining context (see also Section 5.5.1), where spatially distributed data is used for knowledge exchange via dynamic models.
- **Transfer learning:** transfer learning addresses a similar learning problem as dynamic data mining, where already trained models are updated based on samples loaded from a new data source. The difference to dynamic data mining is basically that models are adjusted to new test objects, devices or environments in order to include the new information — this can also stem from temporal changes and is not necessarily triggered by spatially distributed data sources. Data samples may be given different weights for different devices, objects etc.
- **Combination of EFS with other machine learning techniques:** currently, EFS have hardly been studied in the context of incremental learning in combination with other machine learning methods. We see this as an important and useful future challenge, as both parties, the (evolving) fuzzy systems as well as the machine learning community may benefit from such an exchange w.r.t. learning aspects, model components or parameter adaptation and tuning, enriching the diversity of data-driven methodologies in today's real-world systems.

References

1. Abonyi, J.: Fuzzy Model Identification for Control. Birkhäuser, Boston (2003)
2. Abraham, W., Robins, A.: Memory retention – the synaptic stability versus plasticity dilemma. *Trends in Neurosciences* 28(2), 73–78 (2005)
3. Abramovic, M., Stegun, I.: Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables. Dover Publications, New York (1970)
4. Adams, D.E.: Health Monitoring of Structural Materials and Components. John Wiley & Sons, Chichester (2007)
5. Aggarwal, C., Yu, P.: Outlier detection for high dimensional data. In: Proceedings of the 2001 ACM SIGMOD International Conference on Management of Data, Santa Barbara, California, pp. 37–46 (2001)
6. Aha, D.: Lazy Learning. Kluwer Academic Publishers, Norwell (1997)
7. Aha, D., Kibler, D., Albert, M.: Instance-based learning algorithms. *Machine Learning* 6(1), 37–66 (1991)
8. Albertos, P., Sala, A.: Fault detection via continuous-time parameter estimation. In: Proceedings of IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes, SAFEPROCESS, pp. 87–92. Helsinki Univ. Technol., Espoo, Finland (1994)
9. Alsabti, K., Ranka, S., Singh, V.: An efficient k-means clustering algorithm. In: Proceedings of IPPS/SPDP Workshop on High Performance Data Mining, Orlando, Florida, pp. 556–560 (1998)
10. Angelov, P.: Evolving takagi-sugeno fuzzy systems from streaming data, eTS+. In: Angelov, P., Filev, D., Kasabov, N. (eds.) *Evolving Intelligent Systems: Methodology and Applications*, pp. 21–50. John Wiley & Sons, New York (2010)
11. Angelov, P., Filev, D.: An approach to online identification of Takagi-Sugeno fuzzy models. *IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics* 34(1), 484–498 (2004)
12. Angelov, P., Filev, D.: Simpl_eTS: A simplified method for learning evolving Takagi-Sugeno fuzzy models. In: Proceedings of FUZZ-IEEE 2005, Reno, Nevada, U.S.A., pp. 1068–1073 (2005)
13. Angelov, P., Giglio, V., Guardiola, C., Lughofer, E., Luján, J.: An approach to model-based fault detection in industrial measurement systems with application to engine test benches. *Measurement Science and Technology* 17(7), 1809–1818 (2006)

14. Angelov, P., Kasabov, N.: Evolving computational intelligence systems. In: Proceedings of the 1st International Workshop on Genetic Fuzzy Systems, Granada, Spain, pp. 76–82 (2005)
15. Angelov, P., Kordon, A.: Evolving inferential sensors in the chemical process industry. In: Angelov, P., Filev, D., Kasabov, N. (eds.) *Evolving Intelligent Systems: Methodology and Applications*, pp. 313–336. John Wiley & Sons, New York (2010)
16. Angelov, P., Lughofer, E.: Data-driven evolving fuzzy systems using eTS and FLEX-FIS: Comparative analysis. *International Journal of General Systems* 37(1), 45–67 (2008)
17. Angelov, P., Lughofer, E., Klement, E.: Two approaches to data-driven design of evolving fuzzy systems: eTS and FLEXFIS. In: *Proceedings of NAFIPS 2005*, Ann Arbor, Michigan, U.S.A., pp. 31–35 (2005)
18. Angelov, P., Lughofer, E., Zhou, X.: Evolving fuzzy classifiers using different model architectures. *Fuzzy Sets and Systems* 159(23), 3160–3182 (2008)
19. Angelov, P., Xydeas, C., Filev, D.: Online identification of MIMO evolving Takagi-Sugeno fuzzy models. In: *Proceedings of IJCNN-FUZZ-IEEE 2004*, Budapest, Hungary, pp. 55–60 (2004)
20. Angelov, P., Zhou, X.: Evolving fuzzy-rule-based classifiers from data streams. *IEEE Transactions on Fuzzy Systems* 16(6), 1462–1475 (2008)
21. Angelov, P., Zhou, X., Filev, D., Lughofer, E.: Architectures for evolving fuzzy rule-based classifiers. In: *Proceedings of SMC 2007*, Montreal, Canada, pp. 2050–2055 (2007)
22. Angelov, P., Zhou, X.W.: Evolving fuzzy systems from data streams in real-time. In: *2006 International Symposium on Evolving Fuzzy Systems (EFS 2006)*, Ambleside, Lake District, UK, pp. 29–35 (2006)
23. Ariew, R.: *Ockham's Razor: A Historical and Philosophical Analysis of Ockham's Principle of Parsimony*. Champaign-Urbana, University of Illinois, Urbana (1976)
24. Arrègle, J., López, J., Guardiola, C., Monin, C.: Sensitivity study of a NO_x estimation model for on-board applications. SAE paper 2008-01-0640 (2008)
25. Aström, K., Wittenmark, B.: *Adaptive Control*, 2nd edn. Addison-Wesley Longman Publishing Co., Inc., Boston (1994)
26. Atkeson, C., Moore, A., Schaal, S.: Locally weighted learning. *Artificial Intelligence Review* 11(1-5), 11–73 (1997)
27. Avriel, M.: *Nonlinear Programming: Analysis and Methods*. Dover Publishing, New York (2003)
28. Babuska, R.: *Fuzzy Modeling for Control*. Kluwer Academic Publishers, Norwell (1998)
29. Babuska, R., Verbruggen, H.: Constructing fuzzy models by product space clustering. In: Hellendoorn, H., Driankov, D. (eds.) *Fuzzy Model Identification: Selected Approaches*, pp. 53–90. Springer, Berlin (1997)
30. Backer, S.D., Scheunders, P.: Texture segmentation by frequency-sensitive elliptical competitive learning. *Image and Vision Computing* 19(9-10), 639–648 (2001)
31. Baczynski, M., Jayaram, B.: *Fuzzy Implications*. Springer, Heidelberg (2008)
32. Bakushinskii, A.: The problem of the convergence of the iteratively regularized gauss-newton method. *Comput. Math. Phys.* 32(9), 1353–1359
33. Baldi, P., Brunak, S.: *Bioinformatics - A Machine Learning Approach*. MIT Press, Cambridge (2001)
34. Basseville, M., Nikiforov, I.: *Detection of Abrupt Changes*. Prentice Hall Inc., Englewood Cliffs (1993)

35. Bauer, F.: Some considerations concerning regularization and parameter choice algorithms. *Inverse Problems* 23(2), 837–858 (2007)
36. Bauer, F., Kindermann, S.: The quasi-optimality criterion for classical inverse problems. *Inverse Problems* 24(3), 35,002–35,021 (2008)
37. Bauer, F., Lukas, M.: Comparing parameter choice methods for regularization of ill-posed problems. *Inverse Problems* (2010), <http://bmath.de/Docs/mainLowRes.pdf>
38. Bay, S., Saito, K., Ueda, N., Langley, P.: A framework for discovering anomalous regimes in multivariate time-series data with local models. In: *Symposium on Machine Learning for Anomaly Detection*, Stanford, U.S.A. (2004)
39. Bellman, R.: *Dynamic Programming*. Princeton University Press, Princeton (1957)
40. Berenji, H., Ruspini, E.: Experiments in multiobjective fuzzy control of hybrid automotive engines. In: *Proceedings of the Fifth IEEE International Conference on Fuzzy Systems FUZZ-IEEE 1996*, New York, U.S.A., pp. 681–686 (1996)
41. Bergen, J.R., Landy, M.S.: Computational modeling of visual texture segregation. In: Landy, M.S., Movshon, J.A. (eds.) *Computational Models of Visual Processing*, pp. 253–271. MIT Press, Cambridge (1991)
42. Berger, J.: *Statistical Decision Theory and Bayesian Analysis*. Springer, Heidelberg (1985)
43. Beringer, J., Hüllermeier, E.: Online clustering of parallel data streams. *Data & Knowledge Engineering* 58(2), 180–204 (2006)
44. Beringer, J., Hüllermeier, E.: Efficient instance-based learning on data streams. *Intelligent Data Analysis* 11(6), 627–650 (2007)
45. Bernieri, A., Betta, G., Liguori, C.: On-line fault detection and diagnosis obtained by implementing neural algorithms on a digital signal processor. *IEEE Transactions on Instrumentation and Measurement* 45(5), 894–899 (1996)
46. Bezdek, J.: *Pattern Recognition with Fuzzy Objective Function Algorithms*. Kluwer Academic/Plenum Publishers, U.S.A. (1981)
47. Bharitkar, S., Filev, D.: An online learning vector quantization algorithm. In: *Proc. of Sixth International Symposium on Signal Processing and its Applications*, vol. 2, pp. 394–397 (2001)
48. Bie, T.D., Cristianini, N.: Semi-supervised learning using semi-definite programming. In: Chapelle, O., Schoelkopf, B., Zien, A. (eds.) *Semi-Supervised Learning*, pp. 113–131. MIT Press, Cambridge (2006)
49. Biehl, M., Gosh, A., Hammer, B.: Dynamics and generalization ability of LVQ algorithms. *Journal of Machine Learning Research* 8, 323–360 (2007)
50. Birattari, M., Bontempi, G.: *The lazy learning toolbox* (1999), <ftp://iridia.ulb.ac.be/pub/lazy/papers/IridiaTr1999-07.ps.gz>
51. Blazquez, J.M., Shen, Q.: Regaining comprehensibility of approximative fuzzy models via the use of linguistic hedges. In: Casillas, J., Cordon, O., Herrera, F., Magdalena, L. (eds.) *Interpretability Issues in Fuzzy Modeling*, pp. 25–53. Springer, Berlin (2003)
52. Blum, A., Mitchell, T.: Combining labelled and unlabelled data with co-training. In: *Proceedings of the Workshop on Computational Learning Theory (COLT)*, Madison, Wisconsin, pp. 92–100 (1998)
53. Botzheim, J., Cabrita, C., Kóczy, L., Ruano, A.: Estimating fuzzy membership functions parameters by the Levenberg-Marquardt algorithm. In: *Proceedings of the IEEE International Conference on Fuzzy Systems, FUZZ-IEEE 2004*, Budapest, Hungary, pp. 1667–1672 (2004)

54. Botzheim, J., Lughofer, E., Klement, E., Kóczy, L., Gedeon, T.: Separated antecedent and consequent learning for Takagi-Sugeno fuzzy systems. In: Proceedings of FUZZ-IEEE 2006, Vancouver, Canada, pp. 2263–2269 (2006)
55. Bouchachia, A.: Incremental induction of classification fuzzy rules. In: IEEE Workshop on Evolving and Self-Developing Intelligent Systems (ESDIS) 2009, Nashville, U.S.A., pp. 32–39 (2009)
56. Box, G., Jenkins, G., Reinsel, G.: Time Series Analysis, Forecasting and Control. Prentice Hall, Englewood Cliffs (1994)
57. Breiman, L.: Pasting small votes for classification in large databases and on-line. *Machine Learning* 36(1-2), 85–103 (1999)
58. Breiman, L., Friedman, J., Stone, C., Olshen, R.: Classification and Regression Trees. Chapman and Hall, Boca Raton (1993)
59. Brereton, R.: Chemometrics: Data Analysis for the Laboratory and Chemical Plant. John Wiley & Sons, Hoboken (2003)
60. Brown, K.: Voronoi diagrams from convex hulls. *Information Processing Letters* 9(5), 223–228 (1979)
61. Brown, M.P.S., Grundy, W.N., Lin, D., Cristianini, N., Sugnet, C.W., Furey, T.S., Ares, M., Haussler, D.: Knowledge-based analysis of microarray gene expression data by using support vector machines. *Proceedings National Academic Sciences* 97, 262–267 (2006)
62. Burger, M., Haslinger, J., Bodenhofer, U., Engl, H.W.: Regularized data-driven construction of fuzzy controllers. *Journal of Inverse and Ill-Posed Problems* 10(4), 319–344 (2002)
63. Camacho, E., Bordons, C.: Model Predictive Control. Springer, London (2004)
64. Campbell, J., Hashim, A., Murtagh, F.: Flaw detection in woven textiles using space-dependent fourier transform. In: Proc. of ISSC 1997, Irish Signals and Systems Conference, pp. 241–252. University of Ulster, Londonderry (1997)
65. Carmona, P., Castro, J., Zurita, J.: Contradiction sensitive fuzzy model-based adaptive control. *Approximate Reasoning* 30(2), 107–129 (2001)
66. Carpenter, G.A., Grossberg, S.: Adaptive resonance theory (ART). In: Arbib, M.A. (ed.) *The Handbook of Brain Theory and Neural Networks*, pp. 79–82. MIT Press, Cambridge (1995)
67. Carreira-Perpinan, M.: A review of dimension reduction techniques. Tech. Rep. CS-96-09, Dept. of Computer Science. University of Sheffield, Sheffield, U.K (1997)
68. Caruana, R.: Multitask learning: A knowledge-based source of inductive bias. *Machine Learning* 28(1), 41–75 (1997)
69. Casillas, J., Cordon, O., Herrera, F., Magdalena, L.: Interpretability Issues in Fuzzy Modeling. Springer, Heidelberg (2003)
70. Casillas, J., Cordon, O., Jesus, M.D., Herrera, F.: Genetic feature selection in a fuzzy rule-based classification system learning process for high-dimensional problems. *Information Sciences* 136(1-4), 135–157 (2001)
71. Castillo, E., Alvarez, E.: Expert Systems: Uncertainty and Learning. Computational Mechanics Publications, Southampton Boston (1991)
72. Castro, J., Delgado, M.: Fuzzy systems with defuzzification are universal approximators. *IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics* 26(1), 149–152 (1996)
73. Celikyilmaz, A., Türksen, I.: Modeling Uncertainty with Fuzzy Logic: With Recent Theory and Applications. Springer, Berlin (2009)
74. Cernuda, C.: Experimental analysis on assessing interpretability of fuzzy rule-based systems. Universidad de Oviedo, Spain (2010)

75. Chang, C.I.: *Hyperspectral Data Exploration: Theory and Applications*. John Wiley & Sons, Hoboken (2007)
76. Chao, C., Chen, Y., Teng, C.: Simplification of fuzzy-neural systems using similarity analysis. *IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics* 26(2), 344–354 (1996)
77. Chapelle, O., Schoelkopf, B., Zien, A.: *Semi-Supervised Learning*. MIT Press, Cambridge (2006)
78. Chen, J., Patton, R.: *Robust Model-Based Fault Diagnosis for Dynamic Systems*. Kluwer Academic Publishers, Norwell (1999)
79. Chen, M., Linkens, D.: Rule-base self-generation and simplification for data-driven fuzzy models. *Fuzzy Sets and Systems* 142(2), 243–265 (2004)
80. Chen, S., Donoho, D., Saunders, M.: Atomic decomposition by basis pursuit. *SIAM Review* 43(1), 129–159 (2001)
81. Cherry, A., Jones, R.: Fuzzy logic control of an automotive suspension system. *IEEE Proceedings Control Theory and Applications* 142, 149–160 (1995)
82. Chiang, L., Russell, E., Braatz, R.: *Fault Detection and Diagnosis in Industrial Systems*. Springer, Heidelberg (2001)
83. Chiu, S.: Fuzzy model identification based on cluster estimation. *Journal of Intelligent and Fuzzy Systems* 2(3), 267–278 (1994)
84. Chuang, Y., Chen, L.: How to evaluate 100 visual stimuli efficiently. *International Journal of Design* 2(1), 31–43 (2008)
85. Cleveland, W.: Robust locally weighted regression and smoothing scatterplots. *Journal of the American Statistical Association* 74(368), 829–836 (1979)
86. Cohen, F., Fan, Z., Attali, S.: Automated inspection of textile fabrics using textural models. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 13(8), 803–808 (1991)
87. Cohn, D., Atlas, L., Ladner, R.: Improving generalization with active learning. *Machine Learning* 15(2), 201–221 (1994)
88. Collins, M., Schapire, R., Singer, Y.: Logistic regression, adaboost and bregman distances. *Machine Learning* 48(1-3), 253–285 (2002)
89. Condurache, A.: A two-stage-classifier for defect classification in optical media inspection. In: *Proceedings of the 16th International Conference on Pattern Recognition (ICPR 2002)*, Quebec City, Canada, vol. 4, pp. 373–376 (2002)
90. Constantinescu, C., Storer, A.J.: Online adaptive vector quantization with variable size codebook entries. *Information Processing & Management* 30(6), 745–758 (1994)
91. Crawford, S.: Extensions to the CART algorithm. *International Journal of Man-Machine Studies* 31(2), 197–217 (1989)
92. Crespo, F., Weber, R.: A methodology for dynamic data mining based on fuzzy clustering. *Fuzzy Sets and Systems* 150(2), 267–284 (2005)
93. Culp, M., Michailidis, G.: An iterative algorithm for extended learners to a semi-supervised setting. *Journal of Computational and Graphical Statistics* 17(3), 545–571 (2008)
94. Dagan, I., Engelson, S.: Committee-based sampling for training probabilistic classifier. In: *Proceedings of 12th International Conference on Machine Learning*, pp. 150–157 (1995)
95. Dara, R., Kremer, S., Stacey, D.: Clustering unlabeled data with SOMs improves classification of labeled real-world data. In: *Proceedings of the 2002 International Joint Conference on Neural Networks (IJCNN 2002)*, Honolulu, Hawaii, pp. 2237–2242 (2002)
96. Daubechies, I., Defrise, M., Mol, C.D.: An iterative thresholding algorithm for linear inverse problems with a sparsity constraint. *Communications on Pure and Applied Mathematics* 57(11), 1413–1457 (2004)

97. Delany, S.J., Cunningham, P., Tsymbal, A., Coyle, L.: A case-based technique for tracking concept drift in spam filtering. *Knowledge-Based Systems* 18(4-5), 187–195 (2005)
98. Delgado, M.R., Zuben, F.V., Gomide, F.: Hierarchical genetic fuzzy systems: accuracy, interpretability and design autonomy. In: Casillas, J., Cordón, O., Herrera, F., Magdalena, L. (eds.) *Interpretability Issues in Fuzzy Modeling*, pp. 379–405. Springer, Berlin (2003)
99. Demant, C., Streicher-Abel, B., Waszkewitz, P.: *Industrial Image Processing: Visual Quality Control in Manufacturing*. Springer, Heidelberg (1999)
100. Demiriz, A., Bennett, K., Embrechts, M.: Semi-supervised clustering using genetic algorithms. In: *Proceedings of the Artificial Neural Networks in Engineering (ANNIE 1999)*, St. Louis, Missouri, pp. 809–814 (1999)
101. Dempster, A., Laird, N., Rubin, D.: Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society, Series B* 39(1), 1–38 (1977)
102. Diehl, C., Cauwenberghs, G.: SVM incremental learning, adaptation and optimization. In: *Proceedings of the International Joint Conference on Neural Networks*, Boston, vol. 4, pp. 2685–2690 (2003)
103. Dietterich, T.: Ensemble methods in machine learning. In: Kittler, J., Roli, F. (eds.) *MCS 2000. LNCS*, vol. 1857, pp. 1–15. Springer, Heidelberg (2000)
104. Donoho, D., Johnstone, I.: Minimax estimation via wavelet shrinkage. *Annual Statistics* 26(3), 879–921 (1998)
105. Dorf, R., Bishop, R.: *Modern Control Systems*, 11th edn. Prentice Hall, Upper Saddle River (2007)
106. Douglas, S.: Efficient approximate implementations of the fast affine projection algorithm using orthogonal transforms. In: *Proceedings of the IEEE International Conference on Acoustic, Speech and Signal Processing*, Atlanta, Georgia, pp. 1656–1659 (1996)
107. Dragomir, S.: A survey on Cauchy-Bunyakovsky-Schwarz type discrete inequalities. *Journal of Inequalities in Pure and Applied Mathematics* 4(3), 142 (2003)
108. Draper, N., Smith, H.: *Applied Regression Analysis. Probability and Mathematical Statistics*. John Wiley & Sons, New York (1981)
109. Dubois, D., Huellermeier, E., Prade, H.: Towards the representation of implication-based fuzzy rules in terms of crisp rules. In: *Proceedings of the 9th Joint IFSA World Congress and 20th NAFIPS International Conference*, Vancouver, Canada, vol. 3, pp. 1592–1597 (2001)
110. Dubois, D., Prade, H., Ughetto, L.: Checking the coherence and redundancy of fuzzy knowledge bases. *IEEE Transactions on Fuzzy Systems* 5(3), 398–417 (1997)
111. Duda, R., Hart, P., Stork, D.: *Pattern Classification*, 2nd edn. Wiley-Interscience (John Wiley & Sons), Southern Gate, Chichester, West Sussex, England (2000)
112. Dy, J., Brodley, C.: Feature selection for unsupervised learning. *Journal of Machine Learning Research* 5, 845–889 (2004)
113. Economou, C., Morari, M., Palsson, P.: Internal model control: Extension to nonlinear systems. *Industrial & Engineering Chemistry Process Design and Development* 25(2), 403–411 (1986)
114. Efendic, H., Re, L.D.: Automatic iterative fault diagnosis approach for complex systems. *WSEAS Transactions on Systems* 5(2), 360–367 (2006)
115. Efendic, H., Schrempf, A., Re, L.D.: Data based fault isolation in complex measurement systems using models on demand. In: *Proceedings of the IFAC-Safeprocess 2003, IFAC*, Washington D.C., USA, pp. 1149–1154 (2003)
116. Efron, B., Tibshirani, R.: *An Introduction to the Bootstrap*. Chapman and Hall/CRC (1993)

117. Eitzinger, C., Gmainer, M., Heidl, W., Lughofer, E.: Increasing classification performance with adaptive features. In: Gasteratos, A., Vincze, M., Tsotsos, J. (eds.) ICVS 2008. LNCS, vol. 5008, pp. 445–453. Springer, Heidelberg (2008)
118. Eitzinger, C., Heidl, W., Lughofer, E., Raiser, S., Smith, J., Tahir, M., Sannen, D., van Brussel, H.: Assessment of the influence of adaptive components in trainable surface inspection systems. *Machine Vision and Applications* 21(5), 613–626 (2010)
119. Elgammal, A., Duraiswami, R., Harwood, D., Davis, L.: Background and foreground modeling using nonparametric kernel density estimation for visual surveillance. *Proceedings of the IEEE* 90(7), 1151–1163 (2002)
120. Engl, H., Hanke, M., Neubauer, A.: *Regularization of Inverse Problems*. Kluwer Academic Publishers, Dordrecht (1996)
121. Espinosa, J., Vandewalle, J.: Constructing fuzzy models with linguistic integrity from numerical data - AFRELI algorithm. *IEEE Transactions on Fuzzy Systems* 8(5), 591–600 (2000)
122. Espinosa, J., Wertz, V., Vandewalle, J.: *Fuzzy Logic, Identification and Predictive Control (Advances in Industrial Control)*. Springer, Berlin (2004)
123. Ester, M., Kriegel, H., Sander, J., Xu, X.: A density-based algorithm for discovering clusters in large spatial databases with noise. In: *Proceedings of 2nd International Conference on Knowledge Discovery and Data Mining (KDD 1996)*, Portland, Oregon, pp. 226–231 (1996)
124. Eykhoff, P.: *System Identification: Parameter and State Estimation*. John Wiley & Sons, Chichester (1974)
125. Fang, C., Ge, W., Xiao, D.: Fault detection and isolation for linear systems using detection observers. In: Patton, R., Frank, P., Clark, R. (eds.) *Issues of Fault Diagnosis for Dynamic Systems*, pp. 87–113. Springer, Heidelberg (2000)
126. Fernald, A., Kuhl, P.: Acoustic determinants of infant preference for motherese speech. *Infant Behavior and Development* 10(3), 279–293 (1987)
127. Fink, A., Fischer, M., Nelles, O., Isermann, R.: Supervision of nonlinear adaptive controllers based on fuzzy models. *Journal of Control Engineering Practice* 8(10), 1093–1105 (2000)
128. Fiordaliso, A.: A constrained Takagi-Sugeno fuzzy system that allows for better interpretation and analysis. *Fuzzy Sets and Systems* 118(2), 281–296 (2001)
129. Fortuna, L., Graziani, S., Rizzo, A., Xibilia, M.: *Soft Sensor for Monitoring and Control of Industrial Processes*. Springer, London (2007)
130. Fu, L.: An expert network for DNA sequence analysis. *IEEE Intelligent Systems and Their Application* 14(1), 65–71 (1999)
131. Fujino, A., Ueda, N., Saito, K.: A hybrid generative/discriminative approach to semi-supervised classifier design. In: *Proceedings of the 20th National Conference on Artificial Intelligence (AAAI 2005)*, Pittsburgh, Pennsylvania, pp. 764–769 (2005)
132. Fukumizu, K.: Statistical active learning in multilayer perceptrons. *IEEE Transactions on Neural Networks* 11(1), 17–26 (2000)
133. Fukunaga, K.: *Statistical Pattern Recognition*, 2nd edn. Academic Press, San Diego (1990)
134. Fuller, R.: *Introduction to Neuro-Fuzzy Systems*. Physica-Verlag, Heidelberg (1999)
135. Furuhashi, T., Hasekawa, T., Horikawa, S., Uchikawa, Y.: An adaptive fuzzy controller using fuzzy neural networks. In: *Proceedings Fifth IFSA World Congress*, Seoul, pp. 769–772 (1993)
136. Gama, J., Medas, P., Castillo, G., Rodrigues, P.: Learning with drift detection. In: Bazzan, A.L.C., Labidi, S. (eds.) *SBIA 2004*. LNCS (LNAI), vol. 3171, pp. 286–295. Springer, Heidelberg (2004)

137. Garcia, C., Prett, D., Morari, M.: Model predictive control: Theory and practice — a survey. *Automatica* 25(1), 335–348 (1989)
138. Gardiner, D.: *Practical Raman spectroscopy*. Springer, New York (1989)
139. Gay, S.L.: Dynamically regularized fast recursive least squares with application to echo cancellation. In: *Proceedings of the IEEE International Conference on Acoustic, Speech and Signal Processing*, Atlanta, Georgia, pp. 957–960 (1996)
140. Gerla, G.: Approximate reasoning to unify norm-based and implication-based fuzzy control (2009), <http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.144.4468>
141. Gersho, A.: Asymptotically optimal block quantization. *IEEE Transactions on Information Theory* 25(4), 373–380 (1979)
142. Gertler, J.: *Fault Detection and Diagnosis in Engineering Systems*. Marcel Dekker, New York (1998)
143. Giurgiutiu, V.: *Structural Health Monitoring: Fundamentals and Applications: With Piezoelectric Wafer Active Sensors*. Academic Press, San Diego (2007)
144. Goldman, S., Zhou, Y.: Enhanced supervised learning with unlabelled data. In: *Proceedings of the 17th International Conference on Machine Learning*, Stanford, California, pp. 327–334 (2000)
145. Golub, G., Loan, C.V.: *Matrix Computations*, 3rd edn. John Hopkins University Press, Baltimore (1996)
146. Golub, H., Kahan, W.: Calculating the singular values and the pseudo-inverse of a matrix. *Journal of the Society for Industrial and Applied Mathematics: Series B, Numerical Analysis* 2(2), 205–224 (1965)
147. Gonzalez, J., Rojasa, I., Pomaresa, H., Herrera, L., Guillna, A., Palomares, J., Rojasa, F.: Improving the accuracy while preserving the interpretability of fuzzy function approximators by means of multi-objective evolutionary algorithms. *International Journal of Approximate Reasoning* 44(1), 32–44 (2007)
148. Govindhasamy, J., McLoone, S., Irwin, G.: Second-order training of adaptive critics for online process control. *IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics* 35(2), 381–385 (2006)
149. Grahn, H., Geladi, P.: *Techniques and Applications of Hyperspectral Image Analysis*. John Wiley & Sons, Southern Gate (2007)
150. Gray, R.: Vector quantization. *IEEE ASSP Magazine* 1(2), 4–29 (1984)
151. Griesse, R., Lorenz, D.: A semismooth Newton method for Tikhonov functionals with sparsity constraints. *Inverse Problems* 24(3), 035,007 (2008)
152. Groetsch, C.: *The theory of Tikhonov regularization for Fredholm equations of the first kind*, Pitman, Boston (1984)
153. Großböck, W., Lughofer, E., Klement, E.: A comparison of variable selection methods with the main focus on orthogonalization. In: Lopéz-Díaz, M., Gil, M., Grzegorzewski, P., Hryniewicz, O., Lawry, J. (eds.) *Soft Methodology and Random Information Systems, Advances in Soft Computing*, pp. 479–486. Springer, Heidelberg (2004)
154. Groissboeck, W., Lughofer, E., Thumfart, S.: Associating visual textures with human perceptions using genetic algorithms. *Information Sciences* 180(11), 2065–2084 (2010)
155. Grossberg, S.: *Nonlinear neural networks: Principles, mechanisms, and architectures*. *Neural Networks* 1(1), 17–61 (1988)
156. Guillaume, S.: Designing fuzzy inference systems from data: an interpretability-oriented review. *IEEE Transactions on Fuzzy Systems* 9(3), 426–443 (2001)
157. Guo, Y., Woo, P.: Adaptive fuzzy sliding mode control for robotic manipulators. In: *Proceedings of the IEEE CDC Conference 2003, Maui, Hawaii*, pp. 2174–2179 (2003)

158. Gustafson, D., Kessel, W.: Fuzzy clustering with a fuzzy covariance matrix. In: Proceedings of the IEEE CDC Conference 1979, San Diego, CA, USA, pp. 761–766 (1979)
159. Guyon, I., Elisseeff, A.: An introduction to variable and feature selection. *Journal of Machine Learning Research* 3, 1157–1182 (2003)
160. Guyon, I., Gunn, S., Nikravesh, M., Zadeh, L.: *Feature Extraction. Foundations and Applications*. Springer, Heidelberg (2006)
161. Hadamard, J.: Sur les problèmes aux drives partielles et leur signification physique. In: *Princeton University Bulletin*, pp. 49–52 (1902)
162. Haenlein, M., Kaplan, A.: A beginner’s guide to partial least squares (PLS) analysis. *Understanding Statistics* 3(4), 283–297 (2004)
163. Haffari, G., Sarkar, A.: Analysis of semi-supervised learning with the Yarowsky algorithm. In: Proceedings of the 23rd Conference on Uncertainty in Artificial Intelligence (UAI), Vancouver, Canada (2007)
164. Halkidi, M., Batistakis, Y., Vazirgiannis, M.: On clustering validation techniques. *Journal of Intelligent Information Systems* 17(2-3), 107–145 (2001)
165. Hall, P., Martin, R.: Incremental eigenanalysis for classification. In: *British Machine Vision Conference (BMVC) 1998*, Southampton, UK, pp. 286–295 (1998)
166. Hämarik, U., Raus, T.: On the choice of the regularization parameter in ill-posed problems with approximately given noise level of data. *Journal of Inverse and Ill-posed Problems* 14(3), 251–266 (2006)
167. Hamker, F.: RBF learning in a non-stationary environment: the stability-plasticity dilemma. In: Howlett, R., Jain, L. (eds.) *Radial Basis Function Networks 1: Recent Developments in Theory and Applications*, pp. 219–251. Physica Verlag, Heidelberg (2001)
168. Hansen, L., Salamon, P.: Neural network ensembles. *IEEE Transactions on Patterns Analysis and Machine Intelligence* 12(10), 993–1001 (1990)
169. Hansen, P.: The truncated SVD as a method for regularization. *BIT* 27(4), 534–553 (1987)
170. Harrel, F.: *Regression Modeling Strategies*. Springer, New York (2001)
171. Harris, C., Hong, X., Gan, Q.: *Adaptive Modelling, Estimation and Fusion From Data: A Neurofuzzy Approach*. Springer, Berlin (2002)
172. den Hartog, M., Babuska, R., Deketh, H., Grima, M., Verhoef, P., Verbruggen, H.: Knowledge-based fuzzy model for performance prediction of a rock-cutting trencher. *International Journal of Approximate Reasoning* 16(1), 43–66 (1997)
173. Hassibi, B., Stork, D.: Second-order derivatives for network pruning: optimal brain surgeon. In: Hanson, S., Cowan, J., Giles, C. (eds.) *Advances in Neural Information Processing*, vol. 5, pp. 164–171. Morgan Kaufman, Los Altos (1993)
174. Hastie, T., Tibshirani, R., Friedman, J.: *The Elements of Statistical Learning: Data Mining, Inference and Prediction*, 2nd edn. Springer, Heidelberg (2009)
175. Haykin, S.: *Neural Networks: A Comprehensive Foundation*, 2nd edn. Prentice Hall Inc., Upper Saddle River (1999)
176. Hensel, A., Spittel, T.: *Kraft- und Arbeitsbedarf bildsamer Formgebungsverfahren*. VEB Deutscher Verlag für Grundstoffindustrie (1978)
177. Hernandez, N., Talavera, I., Biscay, R., Porroa, D., Ferreira, M.: Support vector regression for functional data in multivariate calibration problems. *Analytica Chimica Acta* 642(1-2), 110–116 (2009)
178. Himmelbauer, J., Drobnics, M.: Regularized numerical optimization of fuzzy rule bases. In: *Proceedings of FUZZ-IEEE 2004*, Budapest, Hungary (2004)
179. Hintermüller, M., Ito, K., Kunisch, K.: The primal-dual active set strategy as a semismooth Newton method. *SIAM Journal on Optimization* 13(3), 865–888 (2003)

180. Ho, W., Tung, W., Quek, C.: An evolving mamdani-takagi-sugeno based neural-fuzzy inference system with improved interpretability-accuracy. In: Proceedings of the WCCI 2010 IEEE World Congress of Computational Intelligence, Barcelona, pp. 682–689 (2010)
181. Holmblad, L., Ostergaard, J.: Control of a cement kiln by fuzzy logic. *Fuzzy Information and Decision Processes*, 398–409 (1982)
182. Hopkins, B.: A new method for determining the type of distribution of plant individuals. *Annals of Botany* 18, 213–226 (1954)
183. Howieson, I., Normand, E., McCulloch, M.: Quantum-cascade lasers smell success. *Laser Focus World* 41(3) (2005)
184. Huang, G., Saratchandran, P., Sundararajan, N.: An efficient sequential learning algorithm for growing and pruning RBF (GAP-RBF) networks. *IEEE Transactions on Systems, Man and Cybernetics Part B: Cybernetics* 34(6), 2284–2292 (2004)
185. Hühn, J., Hüllermeier, E.: FR3: A fuzzy rule learner for inducing reliable classifiers. *IEEE Transactions on Fuzzy Systems* 17(1), 138–149 (2009)
186. Humphrey, M., Cunningham, S., Witten, I.: Knowledge visualization techniques for machine learning. *Intelligent Data Analysis* 2(1-4), 333–347 (1998)
187. Hunt, K., Haas, R., Murray-Smith, R.: Extending the functional equivalence of radial basis function networks and fuzzy inference systems. *IEEE Transactions on Neural Networks* 7(3), 776–781 (1996)
188. Iivarinen, J., Visa, A.: An adaptive texture and shape based defect classification. In: Proceedings of the International Conference on Pattern Recognition, Brisbane, Australia, vol. 1, pp. 117–123 (1998)
189. Isermann, R., Ball, P.: Trends in the application of model-based fault detection and diagnosis of technical processes. In: Proceedings of the 13th IFAC World Congress, pp. 1–12. IEEE Press, San Francisco (1996)
190. Jacobs, R.H., Haak, K., Thumfart, S., Renken, R., Henson, B., Cornelissen, F.: Judgement space as a stepping stone: Finding the cognitive relationship between texture features and beauty ratings. *Plos One* (2010) (in revision)
191. Jain, A., Dubes, R.: *Algorithms for Clustering Data*. Prentice Hall, Upper Saddle River (1988)
192. Jakubek, S., Hametner, C.: Identification of neuro-fuzzy models using GTLS parameter estimation. *IEEE Transactions on Systems, Man and Cybernetics Part B: Cybernetics* 39(5), 1121–1133 (2009)
193. Jakubek, S., Hametner, C., Keuth, N.: Total least squares in fuzzy system identification: An application to an industrial engine. *Engineering Applications of Artificial Intelligence* 21(8), 1277–1288 (2008)
194. Jang, J.S.: ANFIS: Adaptive-network-based fuzzy inference systems. *IEEE Transactions on Systems, Man and Cybernetics* 23(3), 665–685 (1993)
195. Jang, J.S., Sun, C.T.: Functional equivalence between radial basis function networks and fuzzy inference systems. *IEEE Transactions on Neural Networks* 4(1), 156–159 (1993)
196. Jimenez, F., Gomez-Skarmeta, A.F., Sanchez, G., Roubos, H., Babuska, R.: Accurate, transparent and compact fuzzy models by multi-objective evolutionary algorithms. In: Casillas, J., Cordón, O., Herrera, F., Magdalena, L. (eds.) *Interpretability Issues in Fuzzy Modeling*, pp. 431–451. Springer, Berlin (2003)
197. Jin, Y.: Fuzzy modelling of high dimensional systems: Complexity reduction and interpretability improvement. *IEEE Transactions on Fuzzy Systems* 8(2), 212–221 (2000)
198. Jin, Y., Seelen, W., Sendhoff, B.: On generating FC³ fuzzy rule systems from data using evolution strategies. *IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics* 29(6), 829–845 (1999)

199. Jin, Y., Wang, L.: *Fuzzy Systems in Bioinformatics and Computational Biology*. Springer, Berlin (2009)
200. Johansen, T., Babuska, R.: Multiobjective identification of Takagi-Sugeno fuzzy models. *IEEE Transactions on Fuzzy Systems* 11(6), 847–860 (2003)
201. Jolliffe, I.: *Principal Component Analysis*. Springer, Heidelberg (2002)
202. Juang, C., Lin, C.: An on-line self-constructing neural fuzzy inference network and its applications. *IEEE Transactions on Fuzzy Systems* 6(1), 12–32 (1998)
203. Juang, C., Tsao, Y.: A self-evolving interval type-2 fuzzy neural network with on-line structure and parameter learning. *IEEE Transactions on Fuzzy Systems* 16(6), 1411–1424 (2008)
204. Julesz, B.: Experiments in the visual perception of texture. *Scientific American* 232(4), 34–43 (1975)
205. Kalman, R.: A new approach to linear filtering and prediction problems. *Transaction of the ASME, Journal of Basic Engineering* 82, 35–45 (1960)
206. Kang, S., Woo, C., Hwang, H., Woo, K.: Evolutionary design of fuzzy rule base for nonlinear system modelling and control. *IEEE Transactions on Fuzzy Systems* 8(1), 37–45 (2000)
207. Karnik, N., Mendel, J.: Centroid of a type-2 fuzzy set. *Information Sciences* 132(1-4), 195–220 (2001)
208. Kasabov, N.: *Evolving Connectionist Systems - Methods and Applications in Bioinformatics, Brain Study and Intelligent Machines*. Springer, London (2002)
209. Kasabov, N.: *Evolving Connectionist Systems: The Knowledge Engineering Approach*, 2nd edn. Springer, London (2007)
210. Kasabov, N., Zhang, D., Pang, P.: Incremental learning in autonomous systems: evolving connectionist systems for on-line image and speech recognition. In: *Proceedings of IEEE Workshop on Advanced Robotics and its Social Impacts, 2005*, Hsinchu, Taiwan, pp. 120–125 (2005)
211. Kasabov, N.K.: Evolving fuzzy neural networks for supervised/unsupervised online knowledge-based learning. *IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics* 31(6), 902–918 (2001)
212. Kasabov, N.K., Song, Q.: DENFIS: Dynamic evolving neural-fuzzy inference system and its application for time-series prediction. *IEEE Transactions on Fuzzy Systems* 10(2), 144–154 (2002)
213. Kawamoto, N., Soen, T.: Objective evaluation of color design. *Color Research and Application* 18(4), 260–266 (1993)
214. Keogh, E., Lin, J., Fu, A.: HOT SAX: Efficiently finding the most unusual time series subsequence. In: *Proceedings of the 5th IEEE International Conference on Data Mining (ICDM 2005)*, Houston, Texas, pp. 226–233 (2005)
215. Keogh, E., Lonardi, S., Chiu, W.: Finding surprising patterns in a time series database in linear time and space. In: *Proc. of the Eighth ACM SIGKDD Int. Conf. on Knowledge Discovery and Data Mining*, Edmonton, Alberta, Canada, pp. 550–556 (2002)
216. Keogh, E., Lonardi, S., Ratanamahatana, C.: Towards parameter-free data mining. In: *Proc. of the Tenth ACM SIGKDD Int. Conf. on Knowledge Discovery and Data Mining*, Seattle, Washington, pp. 206–215 (2004)
217. Kim, C., Koivo, A.: Hierarchical classification of surface defects on dusty wood boards. *Pattern Recognition Letters* 15(7), 712–713 (1994)
218. Kim, S., Kim, E.Y., Jeong, K., Kim, J.: Emotion-based textile indexing using colors, texture and patterns. In: *Bebis, G., Boyle, R., Parvin, B., Koracin, D., Remagnino, P., Nefian, A., Meenakshisundaram, G., Pascucci, V., Zara, J., Molineros, J., Theisel, H., Malzbender, T. (eds.) ISVC 2006. LNCS, vol. 4292*, pp. 9–18. Springer, Heidelberg (2006)

219. Kindermann, S., Ramlau, R.: Surrogate functionals and thresholding for inverse interface problems. *Journal Inverse Ill-Posed Problems* 15(4), 387–401 (2007)
220. Klement, E., Mesiar, R., Pap, E.: *Triangular Norms*. Kluwer Academic Publishers, Dordrecht (2000)
221. Klinkenberg, R.: Learning drifting concepts: example selection vs. example weighting. *Intelligent Data Analysis* 8(3), 281–300 (2004)
222. Klinkenberg, R., Joachims, T.: Detection concept drift with support vector machines. In: *Proc. of the Seventh International Conference on Machine Learning (ICML)*, San Francisco, CA, U.S.A., pp. 487–494 (2000)
223. Klir, G., Yuan, B.: *Fuzzy Sets and Fuzzy Logic: Theory and Applications*. Prentice Hall PTR, Upper Saddle River (1995)
224. Koch, K.: *Process Analytical Chemistry: Control, Optimization, Quality, Economy*. Springer, Berlin (1999)
225. Koczy, L., Tikk, D., Gedeon, T.: On functional equivalence of certain fuzzy controllers and RBF type approximation schemes. *International Journal of Fuzzy Systems* 2(3), 164–175 (2000)
226. Kohonen, T.: An introduction to neural computing. *Neural Networks* 1(1), 3–16 (1988)
227. Kohonen, T.: *Self-Organizing Maps: second extended edition*. Springer, Heidelberg (1995)
228. Kohonen, T., Barna, G., Chrisley, R.: Statistical pattern recognition with neural networks: Benchmarking studies. In: *Proceedings of the IEEE International Conference on Neural Networks*, San Diego, California, pp. 61–68 (1988)
229. Korbicz, J., Koscielny, J., Kowalczyk, Z., Cholewa, W.: *Fault Diagnosis - Models, Artificial Intelligence and Applications*. Springer, Heidelberg (2004)
230. Kordon, A., Smits, G.: Soft sensor development using genetic programming. In: *Proceedings GECCO 2001*, San Francisco, pp. 1346–1351 (2001)
231. Kordon, A., Smits, G., Kalos, A., Jordaan, E.: Robust soft sensor development using genetic programming. In: Leardi, R. (ed.) *Nature-Inspired Methods in Chemometrics*, pp. 69–108 (2003)
232. Kowalski, B., McLennan, F.: *Process Analytical Chemistry*. Springer, Netherlands (1995)
233. Krishnapuram, R., Freg, C.: Fitting an unknown number of lines and planes to image data through compatible cluster merging. *Pattern Recognition* 25(4), 385–400 (1992)
234. Krogh, A., Vedelsby, J.: Neural network ensembles, cross validation, and active learning. In: Tesauro, I.G., Touretzky, D., Leen, T. (eds.) *Advances in Neural Information Processing Systems*, vol. 7, pp. 231–238 (1995)
235. Kruse, R., Gebhardt, J., Palm, R.: *Fuzzy Systems in Computer Science*. Verlag Vieweg, Wiesbaden (1994)
236. Kuncheva, L.: *Fuzzy Classifier Design*. Physica-Verlag, Heidelberg (2000)
237. Kuncheva, L.: *Combining pattern classifiers: Methods and algorithms*. Wiley-Interscience (John Wiley & Sons), Southern Gate (2004)
238. Kuncheva, L.I., Bezdek, J.C., Duin, R.P.W.: Decision templates for multiple classifier fusion: an experimental comparison. *Pattern Recognition* 34(2), 299–314 (2001)
239. Kurzhanskiy, A.A., Varaiya, P.: Ellipsoidal toolbox. Tech. rep. (2006)
240. Lam, C.: Emotion modelling using neural network. Universiti Utara, Malaysia (2005)
241. Lee, C.: Fuzzy logic in control systems: fuzzy logic controller - part i and ii. *IEEE Transactions on Systems, Man and Cybernetics* 20(2), 404–435 (1990)
242. Lemos, A., Caminhas, W., Gomide, F.: Fuzzy multivariable gaussian evolving approach for fault detection and diagnosis. In: Hüllermeier, E., Kruse, R., Hoffmann, F. (eds.) *IPMU 2010. LNCS*, vol. 6178, pp. 360–369. Springer, Heidelberg (2010)

243. Lendasse, A., Francois, D., Wertz, V., Verleysen, M.: Vector quantization: A weighted version for time-series forecasting. *Future Generation Computer Systems* 21(7), 1056–1067 (2005)
244. Leng, G., McGinnity, T., Prasad, G.: An approach for on-line extraction of fuzzy rules using a self-organising fuzzy neural network. *Fuzzy Sets and Systems* 150(2), 211–243 (2005)
245. Leng, G., Prasad, G., McGinnity, T.: An new approach to generate a self-organizing fuzzy neural network model. In: *Proceedings of the International Conference of Systems, Man and Cybernetics, Hammamet, Tunisia* (2002)
246. Leng, G., Prasad, G., McGinnity, T.: An on-line algorithm for creating self-organizing fuzzy neural networks. *Neural Networks* 17(10), 1477–1493 (2004)
247. Leondes, C.: *Fuzzy Logic and Expert Systems Applications (Neural Network Systems Techniques and Applications)*. Academic Press, San Diego (1998)
248. Lepskij, O.: On a problem of adaptive estimation in gaussian white noise. *Theory of Probability and its Applications* 35(3), 454–466 (1990)
249. Leung, C., Wong, K., Sum, P., Chan, L.: A pruning method for the recursive least squares algorithm. *Neural Networks* 14(2), 147–174 (2001)
250. Lewis, D., Catlett, J.: Heterogeneous uncertainty sampling for supervised learning. In: *Proceedings of the 11th International Conference on Machine Learning, New Brunswick, New Jersey*, pp. 148–156 (1994)
251. Li, X., Li, H., Guan, X., Du, R.: Fuzzy estimation of feed-cutting force from current measurement - a case study on tool wear monitoring. *IEEE Transactions Systems, Man, and Cybernetics Part C: Applications and Reviews* 34(4), 506–512 (2004)
252. Li, X., Tso, S.K.: Drill wear monitoring with current signal. *Wear* 231(2), 172–178 (1999)
253. Li, X., Wang, L., Sung, E.: Multilabel SVM active learning for image classification. In: *Proceedings of the International Conference on Image Processing (ICIP), Singapore*, vol. 4, pp. 2207–2010 (2004)
254. Li, Y.: On incremental and robust subspace learning. *Pattern Recognition* 37(7), 1509–1518 (2004)
255. Liang, Q., Mendel, J.: Interval type-2 fuzzy logic systems: Theory and design. *IEEE Transactions on Fuzzy Systems* 8(5), 535–550 (2000)
256. Lim, C., Harrison, R.: Online pattern classification with multiple neural network systems: An experimental study. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews* 33(2), 235–247 (2003)
257. Lim, R., Phan, M.: Identification of a multistep-ahead observer and its application to predictive control. *Journal of Guidance, Control and Dynamics* 20(6), 1200–1206 (1997)
258. Lima, E., Gomide, F., Ballini, R.: Participatory evolving fuzzy modeling. In: *2nd International Symposium on Evolving Fuzzy Systems, Lake District, UK*, pp. 36–41 (2006)
259. Lima, E., Hell, M., Ballini, R., Gomide, F.: Evolving fuzzy modeling using participatory learning. In: Angelov, P., Filev, D., Kasabov, N. (eds.) *Evolving Intelligent Systems: Methodology and Applications*, pp. 67–86. John Wiley & Sons, New York (2010)
260. Lin, C., Lee, C.: Neural-network-based fuzzy logic control and decision system. *IEEE Transactions on Computation* 40, 1320–1336 (1991)
261. Lin, C., Lee, C.: Reinforcement structure/parameter learning for neural-network-based fuzzy logic control systems. *IEEE Transactions on Fuzzy Systems* 2(1), 46–63 (1994)
262. Lin, C., Lee, C.: *Neuro Fuzzy Systems*. Prentice Hall, Englewood Cliffs (1996)
263. Lin, C., Segel, L.: *Mathematics Applied to Deterministic Problems in the Natural Sciences*. SIAM: Society for Industrial and Applied Mathematics, Philadelphia (1988)

264. Ljung, L.: *System Identification: Theory for the User*. Prentice Hall PTR, Prentice Hall Inc., Upper Saddle River, New Jersey (1999)
265. Lughofer, E.: Process safety enhancements for data-driven evolving fuzzy models. In: *Proceedings of 2nd Symposium on Evolving Fuzzy Systems (EFS 2006)*, Lake District, UK, pp. 42–48 (2006)
266. Lughofer, E.: Evolving vector quantization for classification of on-line data streams. In: *Proc. of the Conference on Computational Intelligence for Modelling, Control and Automation (CIMCA 2008)*, Vienna, Austria, pp. 780–786 (2008)
267. Lughofer, E.: Extensions of vector quantization for incremental clustering. *Pattern Recognition* 41(3), 995–1011 (2008)
268. Lughofer, E.: FLEXFIS: A robust incremental learning approach for evolving TS fuzzy models. *IEEE Transactions on Fuzzy Systems* 16(6), 1393–1410 (2008)
269. Lughofer, E.: On dynamic selection of the most informative samples in classification problems. In: *Proc. of the 9th International Conference in Machine Learning and Applications, ICMLA 2010*. IEEE, Washington D.C. (to appear, 2010)
270. Lughofer, E.: On dynamic soft dimension reduction in evolving fuzzy classifiers. In: Hüllermeier, E., Kruse, R., Hoffmann, F. (eds.) *IPMU 2010*. LNCS, vol. 6178, pp. 79–88. Springer, Heidelberg (2010)
271. Lughofer, E.: On-line evolving image classifiers and their application to surface inspection. *Image and Vision Computing* 28(7), 1063–1172 (2010)
272. Lughofer, E.: On-line feature weighing in evolving fuzzy classifiers. *Fuzzy Sets and Systems* (in press, 2010), doi:10.1016/j.fss.2010.08.012
273. Lughofer, E.: Towards robust evolving fuzzy systems. In: Angelov, P., Filev, D., Kasabov, N. (eds.) *Evolving Intelligent Systems: Methodology and Applications*, pp. 87–126. John Wiley & Sons, New York (2010)
274. Lughofer, E., Angelov, P.: Detecting and reacting on drifts and shifts in on-line data streams with evolving fuzzy systems. In: *Proceedings of the IFSA/EUSFLAT 2009 Conference*, Lisbon, Portugal, pp. 931–937 (2009)
275. Lughofer, E., Angelov, P.: Handling drifts and shifts in on-line data streams with evolving fuzzy systems. *Applied Soft Computing* (in press, 2010), doi:10.1016/j.asoc.2010.07.003
276. Lughofer, E., Angelov, P., Zhou, X.: Evolving single- and multi-model fuzzy classifiers with FLEXFIS-Class. In: *Proceedings of FUZZ-IEEE 2007*, London, UK, pp. 363–368 (2007)
277. Lughofer, E., Bodenhofer, U.: Incremental learning of fuzzy basis function networks with a modified version of vector quantization. In: *Proceedings of IPMU 2006*, Paris, France, vol. 1, pp. 56–63 (2006)
278. Lughofer, E., Efcendic, H., Re, L.D., Klement, E.: Filtering of dynamic measurements in intelligent sensors for fault detection based on data-driven models. In: *Proceedings of the IEEE CDC Conference*, Maui, Hawaii, pp. 463–468 (2003)
279. Lughofer, E., Guardiola, C.: Applying evolving fuzzy models with adaptive local error bars to on-line fault detection. In: *Proceedings of Genetic and Evolving Fuzzy Systems 2008*, pp. 35–40. Witten-Bommerholz, Germany (2008)
280. Lughofer, E., Guardiola, C.: On-line fault detection with data-driven evolving fuzzy models. *Journal of Control and Intelligent Systems* 36(4), 307–317 (2008)
281. Lughofer, E., Hüllermeier, E., Klement, E.: Improving the interpretability of data-driven evolving fuzzy systems. In: *Proceedings of EUSFLAT 2005*, Barcelona, Spain, pp. 28–33 (2005)
282. Lughofer, E., Kindermann, S.: Improving the robustness of data-driven fuzzy systems with regularization. In: *Proc. of the IEEE World Congress on Computational Intelligence (WCCI) 2008*, Hongkong, pp. 703–709 (2008)

283. Lughofer, E., Kindermann, S.: Rule weight optimization and feature selection in fuzzy systems with sparsity constraints. In: Proceedings of the IFSA/EUSFLAT 2009 Conference, Lisbon, Portugal, pp. 950–956 (2009)
284. Lughofer, E., Kindermann, S.: SparseFIS: Data-driven learning of fuzzy systems with sparsity constraints. *IEEE Transactions on Fuzzy Systems* 18(2), 396–411 (2010)
285. Lughofer, E., Klement, E.: Online adaptation of Takagi-Sugeno fuzzy inference systems. In: Proceedings of CESA—IMACS MultiConference, Lille, France (2003)
286. Lughofer, E., Klement, E.: Premise parameter estimation and adaptation in fuzzy systems with open-loop clustering methods. In: Proceedings of FUZZ-IEEE 2004, Budapest, Hungary (2004)
287. Lughofer, E., Klement, E., Lujan, J., Guardiola, C.: Model-based fault detection in multi-sensor measurement systems. In: Proceedings of IEEE IS 2004, Varna, Bulgaria, pp. 184–189 (2004)
288. Lughofer, E., Macian, V., Guardiola, C., Klement, E.: Data-driven design of Takagi-Sugeno fuzzy systems for predicting NOx emissions. In: Hüllermeier, E., Kruse, R., Hoffmann, F. (eds.) *IPMU 2010. Communications in Computer and Information Science*, vol. 81, pp. 1–10. Springer, Heidelberg (2010)
289. Lughofer, E., Smith, J.E., Caleb-Solly, P., Tahir, M., Eitzinger, C., Sannen, D., Nuttin, M.: On human-machine interaction during on-line image classifier training. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans* 39(5), 960–971 (2009)
290. Lukas, M.: Robust generalized cross-validation for choosing the regularization parameter. *Inverse Problems* 22(5), 1883–1902 (2006)
291. Luo, A.: *Discontinuous Dynamical Systems on Time-varying Domains*. Springer, Heidelberg (2009)
292. Macias-Hernandez, J., Angelov, P.: Applications of evolving intelligent systems to the oil and gas industry. In: Angelov, P., Filev, D., Kasabov, N. (eds.) *Evolving Intelligent Systems: Methodology and Applications*, pp. 401–421. John Wiley & Sons, New York (2010)
293. Mackay, D.: Information-based objective functions for active data selection. *Neural Computation* 4(4), 305–318 (1992)
294. Mackey, M., Glass, L.: Oscillation and chaos in physiological control systems. *Science* 197(4300), 287–289 (1977)
295. Mahalanobis, P.C.: On the generalised distance in statistics. *Proceedings of the National Institute of Sciences of India* 2(1), 49–55 (1936)
296. Mahony, S., Hendrix, D., Golden, A., Smith, T.J., Rokhsar, D.S.: Transcription factor binding site identification using the self-organizing map. *Bioinformatics* 21(9), 1807–1814 (2005)
297. Mamdani, E.: Application of fuzzy logic to approximate reasoning using linguistic systems. *Fuzzy Sets and Systems* 26(12), 1182–1191 (1977)
298. Mardia, K., Kent, J., Bibby, J.: *Multivariate Analysis*. Academic Press, New York (1979)
299. Marquardt, D.: An algorithm for least-squares estimation of nonlinear parameters. *SIAM Journal on Applied Mathematics* 11(2), 431–441 (1963)
300. Massart, D., Vandeginste, B., Buydens, L., Jong, S.D., Lewi, P., Smeyer-Verbeke, J.: *Handbook of Chemometrics and Qualimetrics Part A*. Elsevier, Amsterdam (1997)
301. Mastorocostas, P., Theocharis, J., Petridis, V.: A constrained orthogonal least-squares method for generating TSK fuzzy models: application to short-term load forecasting. *Fuzzy Sets and Systems* 118(2), 215–233 (2001)

302. Mendel, J.: *Uncertain Rule-Based Fuzzy Logic Systems: Introduction and New Directions*. Prentice Hall, Upper Saddle River (2001)
303. Mendel, J.: Type-2 fuzzy sets and systems: an overview. *IEEE Computational Intelligence Magazine* 2, 20–29 (2007)
304. Mendel, J., John, R.: Type-2 fuzzy sets made simple. *IEEE Transactions on Fuzzy Systems* 10(2), 117–127 (2002)
305. Merched, R., Sayed, A.: Fast RLS laguerre adaptive filtering. In: *Proceedings of the Allerton Conference on Communication, Control and Computing*, Allerton, IL, pp. 338–347 (1999)
306. Michels, K., Klawonn, F., Kruse, R., Nürnberger, A.: *Fuzzy-Regelung: Grundlagen, Entwurf, Analyse*. Springer, Berlin (2002)
307. Mikenina, L., Zimmermann, H.: Improved feature selection and classification by the 2-additive fuzzy measure. *Fuzzy Sets and Systems* 107(2), 197–218 (1999)
308. Mikut, R., Mäkel, J., Gröll, L.: Interpretability issues in data-based learning of fuzzy systems. *Fuzzy Sets and Systems* 150(2), 179–197 (2005)
309. Miller, A.: *Subset Selection in Regression*, 2nd edn. Chapman and Hall/CRC, Boca Raton, Florida (2002)
310. Miller, G.: The magic number seven plus or minus two: some limits on our capacity for processing information. *Psychological Review* 63(2), 81–97 (1956)
311. Mitchell, T.M.: *Machine Learning*. McGraw-Hill International Editions, Singapore (1997)
312. Moos, R.: A brief overview on automotive exhaust gas sensors based on electroceramics. *International Journal of Applied Ceramic Technology* 2(5), 401–413 (2005)
313. Morant, F., Albertos, P., Martinez, M., Crespo, A., Navarro, J.: RIGAS: An intelligent controller for cement kiln control. In: *Proceedings of the IFAC Symposium on Artificial Intelligence in Real Time Control*. Delft, Netherlands (1992)
314. Morozov, V.A.: On the solution of functional equations by the method of regularization. *Soviet Mathematics Doklady* 7, 414–417 (1966)
315. Muslea, I.: *Active learning with multiple views*. Ph.D. thesis, University of Southern California (2000)
316. Myers, R.: *Classical and Modern Regression with Applications*. PWS-KENT, Boston (1990)
317. Narendra, K., Parthasarathy, K.: Identification and control of dynamic systems using neural networks. *IEEE Transactions on Neural Networks* 1(1), 4–27 (1990)
318. Nauck, D., Kruse, R.: NEFCLASS-X – a soft computing tool to build readable fuzzy classifiers. *BT Technology Journal* 16(3), 180–190 (1998)
319. Nauck, D., Nauck, U., Kruse, R.: Generating classification rules with the neuro-fuzzy system NEFCLASS. In: *Proceedings of the Biennial Conference of the North American Fuzzy Information Processing Society (NAFIPS)*, Berkeley, CA, pp. 466–470 (1996)
320. Nelles, O.: *Nonlinear System Identification*. Springer, Berlin (2001)
321. Ngia, L., Sjöberg, J.: Efficient training of neural nets for nonlinear adaptive filtering using a recursive Levenberg-Marquardt algorithm. *IEEE Trans. Signal Processing* 48(7), 1915–1926 (2000)
322. Nguyen, H., Sugeno, M., Tong, R., Yager, R.: *Theoretical Aspects of Fuzzy Control*. John Wiley & Sons, New York (1995)
323. Nigam, K., Ghani, R.: Analyzing the effectiveness and applicability of co-training. In: *Proceedings of the 9th International Conference on Information and Knowledge Management*, Washington, DC, pp. 86–93 (2000)
324. Nigam, K., McCallum, A., Thrun, S., Mitchell, T.: Text classification from labelled and unlabelled documents using EM. *Machine Learning* 39(2-3), 103–134 (2000)

325. Norman, D.: *Emotional Design: Why We Love (or Hate) Everyday Things?* Basic Books, New York (2003)
326. Nyberg, M.: Model based fault diagnosis, methods, theory, and automotive engine application. Ph.D. thesis, Department of Electrical Engineering Linköping University, SE-581 83 Linköping, Sweden (1999)
327. Oliveira, J.V.D.: A design methodology for fuzzy system interfaces. *IEEE Transactions on Fuzzy Systems* 3(4), 404–414 (1995)
328. Oliveira, J.V.D.: Semantic constraints for membership function optimization. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans* 29(1), 128–138 (1999)
329. Oppenheim, A., Schaffer, R., Buck, J.: *Discrete-Time Signal Processing*, 2nd edn. Prentice Hall, Upper Saddle River (1999)
330. Oza, N.: Online ensemble learning. Ph.D. thesis. University of California, USA (2001)
331. Özdemir, S., Baykut, A., Meylani, R., Erçil, A., Ertüzün, A.: Comparative evaluation of texture analysis algorithms for defect inspection of textile products. In: *Proceedings of the International Conference on Pattern Recognition*, Los Alamitos, CA, pp. 1738–1741 (1998)
332. Pal, N., Chakraborty, D.: Mountain and subtractive clustering method: Improvement and generalizations. *International Journal of Intelligent Systems* 15(4), 329–341 (2000)
333. Palm, R.: Fuzzy controller for a sensor guided robot. *Fuzzy Sets and Systems* 31(2), 133–149 (1989)
334. Pang, S., Ozawa, S., Kasabov, N.: Incremental linear discriminant analysis for classification of data streams. *IEEE Transaction on Systems, Men and Cybernetics, Part B: Cybernetics* 35(5), 905–914 (2005)
335. Papari, G., Petkov, N.: Algorithm that mimics human perceptual grouping of dot patterns. In: *Brain, Vision, and Artificial Intelligence*, pp. 497–506. Springer, Berlin (2005)
336. Pedreira, C.: Learning vector quantization with training data selection. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 28(1), 157–162 (2006)
337. Pedrycz, W.: An identification algorithm in fuzzy relational systems. *Fuzzy Sets and Systems* 13(2), 153–167 (1984)
338. Pedrycz, W.: A dynamic data granulation through adjustable clustering. *Pattern Recognition Letters* 29(16), 2059–2066 (2008)
339. Pedrycz, W., Gomide, F.: *Introduction to Fuzzy Sets*. MIT Press, Cambridge (1998)
340. Pedrycz, W., Rai, P.: Collaborative clustering with the use of fuzzy c-means and its quantification. *Fuzzy Sets and Systems* 159(18), 2399–2427 (2008)
341. Pham, B., Brown, R.: Visualisation of fuzzy systems: requirements, techniques and framework. *Future Generation Computer Systems* 27(7), 1199–1212 (2005)
342. Piegat, A.: *Fuzzy Modeling and Control*. Physica Verlag, Springer, Heidelberg, New York (2001)
343. Poirier, F., Ferrieux, A.: DVQ: Dynamic vector quantization - an incremental LVQ. In: Kohonen, T., Mäkisara, K., Simula, O., Kangas, J. (eds.) *Artificial Neural Networks*, pp. 1333–1336. Elsevier Science Publishers B.V., North-Holland (1991)
344. Polat, K., Günes, S.: A novel hybrid intelligent method based on C4.5 decision tree classifier and one-against-all approach for multi-class classification problems. *Expert Systems with Applications* 36(2), 1587–1592 (2007)
345. Polikar, R.: Ensemble based systems in decision making. *IEEE Circuits and Systems Magazine* 6(3), 21–45 (2006)
346. Prasad, G., Leng, G., McGuinness, T., Coyle, D.: Online identification of self-organizing fuzzy neural networks for modeling time-varying complex systems. In: Angelov, P., Filev, D., Kasabov, N. (eds.) *Evolving Intelligent Systems: Methodology and Applications*, pp. 201–228. John Wiley & Sons, New York (2010)

347. Preparata, F., Hong, S.: Convex hulls of finite sets of points in two and three dimensions. *Communication ACM* 20(2), 87–93 (1977)
348. Press, W., Teukolsky, S., Vetterling, W., Flannery, P.: *Numerical Recipes in C: The Art of Scientific Computing*. Cambridge University Press, Cambridge (1992)
349. Provost, F.: Machine learning from imbalanced data sets. In: *Proceedings of the AAAI Workshop*, Menlo Park, CA, USA, pp. 1–3 (2000)
350. Qin, S., Li, W., Yue, H.: Recursive PCA for adaptive process monitoring. *Journal of Process Control* 10(5), 471–486 (2000)
351. Quinlan, J.R.: *C4.5: Programs for Machine Learning*. Morgan Kaufmann Publishers, San Francisco (1993)
352. Jacobs, R., Jordan, M., Nowlan, S.J., Hinton, G.E.: Adaptive mixtures of local experts. *Neural Computation* 3, 79–87 (1991)
353. Polikar, R., Upda, L., Upda, S.S., Honavar, V.: Learn++: An incremental learning algorithm for supervised neural networks. *EEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews* 31(4), 497–508 (2001)
354. Raghavan, H., Madani, O., Jones, R.: Active learning with feedback on both features and instances. *Journal of Machine Learning Research* 7, 1655–1686 (2006)
355. Raiser, S., Lughofer, E., Eitzinger, C., Smith, J.: Impact of object extraction methods on classification performance in surface inspection systems. *Machine Vision and Applications* 21(5), 627–641 (2010)
356. Rallo, R., Ferre-Gine, J., Arena, A., Girault, F.: Neural virtual sensor for the inferential prediction of product quality from process variables. *Computers and Chemical Engineering* 26(12), 1735–1754 (2004)
357. Ramamurthy, S., Bhatnagar, R.: Tracking recurrent concept drift in streaming data using ensemble classifiers. In: *Proceedings of the Sixth International Conference on Machine Learning and Applications (ICMLA)*, 2007, Cincinnati, Ohio, pp. 404–409 (2007)
358. Ramlau, R., Teschke, G.: A tikhonov-based projection iteration for nonlinear ill-posed problems with sparsity constraints. *Numerische Mathematik* 104(2), 177–203 (2006)
359. Ramos, J., Dourado, A.: Pruning for interpretability of large spanned eTS. In: *Proceedings of the 2006 International Symposium on Evolving Fuzzy Systems (EFS 2006)*, Lake District, UK, pp. 55–60 (2006)
360. Ramos, J.V., Pereira, C., Dourado, A.: The building of interpretable systems in real-time. In: Angelov, P., Filev, D., Kasabov, N. (eds.) *Evolving Intelligent Systems: Methodology and Applications*, pp. 127–150. John Wiley & Sons, New York (2010)
361. Rao, Y., Principe, J., Wong, T.: Fast RLS-like algorithm for generalized eigendecomposition and its applications. *The Journal of VLSI Signal Processing* 37(2-3), 333–344 (2004)
362. Raus, T.: About regularization parameter choice in case of approximately given error bounds of data. In: Vainikko, G. (ed.) *Methods for Solution of Integral Equations and Ill-Posed Problems*, pp. 77–89. Springer, Berlin (1992)
363. Reed, R.: Pruning algorithms - a survey. *IEEE Transactions on Neural Networks* 4(5), 740–747 (1993)
364. Reeves, J., Delwiche, S.: Partial least squares regression for analysis of spectroscopic data. *Journal of Near Infrared Spectroscopy* 11(6), 415–431 (2003)
365. Rehm, F., Klawonn, F., Kruse, R.: Visualization of fuzzy classifiers. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* 15(5), 615–624 (2007)
366. Reinke, R., Michalski, R.: Incremental learning of concept description: A method and experimental results. In: Hayes, J., Michie, D., Richards, J. (eds.) *Machine Intelligence*, vol. 11, pp. 263–288. Oxford University Press, Inc., New York (1988)

367. Rhee, F.H., Choi, B.I.: A convex cluster merging algorithm using support vector machines. In: Proceedings of the 12th IEEE International Conference on Fuzzy Systems, St. Louis, Missouri, vol. 2, pp. 892–895 (2003)
368. Robinson, T., Moyeed, R.: Making robust the cross-validators choice of smoothing parameter in spline smoothing regression. *Communications in Statistics — Theory and Methods* 18(2), 523–539 (1989)
369. Rong, H.J., Sundararajan, N., Huang, G.B., Saratchandran, P.: Sequential adaptive fuzzy inference system (SAFIS) for nonlinear system identification and prediction. *Fuzzy Sets and Systems* 157(9), 1260–1275 (2006)
370. Ros, L., Sabater, A., Thomas, F.: An ellipsoidal calculus based on propagation and fusion. *IEEE Transactions on Systems, Man and Cybernetics - Part B: Cybernetics* 32(4), 430–442 (2002)
371. Rothamsted, V., Lewis, T., Barnett, V.: *Outliers in Statistical Data*. John Wiley & Sons, Chichester (1998)
372. Roubos, H., Setnes, M.: Compact and transparent fuzzy models and classifiers through iterative complexity reduction. *IEEE Transactions on Fuzzy Systems* 9(4), 516–524 (2001)
373. Roubos, J., Setnes, M., Abonyi, J.: Learning fuzzy classification rules from data. *Information Sciences* 150(1-2), 77–93 (2003)
374. Rubio, J.: Stability analysis for an on-line evolving neuro-fuzzy recurrent network. In: Angelov, P., Filev, D., Kasabov, N. (eds.) *Evolving Intelligent Systems: Methodology and Applications*, pp. 173–199. John Wiley & Sons, New York (2010)
375. Rumelhart, D., Hinton, G., Williams, R.: Learning internal representations by error propagation. In: Rumelhart, D., McClelland, J. (eds.) *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, vol. 1, pp. 318–362. MIT Press, Cambridge (1986)
376. Ruspini, E.: A new approach to clustering. *Information and Control* 15(1), 22–32 (1969)
377. Sadeghi-Tehran, P., Angelov, P., Ramezani, R.: A fast recursive approach to autonomous detection, identification and tracking of multiple objects in video streams under uncertainties. In: Hüllermeier, E., Kruse, R., Hoffmann, F. (eds.) *IPMU 2010. Communications in Computer and Information Science*, vol. 81, pp. 30–43. Springer, Heidelberg (2010)
378. Samanta, B.: Gear fault detection using artificial neural networks and support vector machines with genetic algorithms. *Mechanical Systems and Signal Processing* 18(3), 625–644 (2004)
379. Sanchez, L., Suarez, M., Villar, J., Couso, I.: Mutual information-based feature selection and partition design in fuzzy rule-based classifiers from vague data. *International Journal of Approximate Reasoning* 49(3), 607–622 (2008)
380. Sannen, D., Lughofer, E., Brussel, H.V.: Increasing on-line classification performance using incremental classifier fusion. In: *Proc. of International Conference on Adaptive and Intelligent Systems (ICAIS 2009)*, Klagenfurt, Austria, pp. 101–107 (2009)
381. Sannen, D., Lughofer, E., Brussel, H.V.: Towards incremental classifier fusion. *Intelligent Data Analysis* 14(1), 3–30 (2010)
382. Sannen, D., Nuttin, M., Smith, J., Tahir, M., Lughofer, E., Eitzinger, C.: An interactive self-adaptive on-line image classification framework. In: Gasteratos, A., Vincze, M., Tsotsos, J.K. (eds.) *ICVS 2008. LNCS*, vol. 5008, pp. 173–180. Springer, Heidelberg (2008)
383. Sato, A., Yamada, K.: Generalized learning vector quantization. In: Tesauro, G., Touretzky, D., Leon, T. (eds.) *Advances in Neural Information Processing Systems*, vol. 7, pp. 423–429 (1988)

384. Schael, M.: Texture fault detection using invariant textural features. In: Radig, B., Florczyk, S. (eds.) DAGM 2001. LNCS, vol. 2191, pp. 17–24. Springer, Heidelberg (2001)
385. Schaffer, C.: Overfitting avoidance as bias. *Machine Learning* 10(2), 153–178 (1993)
386. Scheier, E., Slaney, M.: Construction and evaluation of a robust multifeature speech/music discriminator. In: Proceedings of the International Conference on Acoustics, Speech, and Signal Processing (ICASSP) 1997, Munich, pp. 1331–1334 (1997)
387. Schmidt, B., Klawonn, F.: Construction of fuzzy classification systems with the Lukaszewicz-t-norm. In: Proceedings of the 19th International Conference of the North American Fuzzy Information Processing Society (NAFIPS), Atlanta, Georgia, pp. 109–113 (2000)
388. Schoener, H., Moser, B., Lughofer, E.: On preprocessing multi-channel data for on-line process monitoring. In: Proc. of the Conference on Computational Intelligence for Modelling, Control and Automation (CIMCA 2008), Vienna, Austria, pp. 414–420 (2008)
389. Schölkopf, B., Smola, A.: *Learning with Kernels - Support Vector Machines, Regularization, Optimization and Beyond*. MIT Press, London (2002)
390. Sebe, N., Lew, M.: Texture features for content-based retrieval. In: Lew, M. (ed.) *Principles of visual information retrieval*, pp. 51–85. Springer, London (2001)
391. Senge, R., Hüllermeier, E.: Pattern trees for regression and fuzzy systems modeling. In: Proc. of the IEEE World Congress on Computational Intelligence. IEEE, Barcelona (2010)
392. Serafim, A.: Segmentation of natural images based on multiresolution pyramids linking: Application to leather defects detection. In: Proceedings of the International Conference on Pattern Recognition, Kobe, Japan, pp. 41–44 (1992)
393. Setnes, M.: Simplification and reduction of fuzzy rules. In: Casillas, J., Cordon, O., Herrera, F., Magdalena, L. (eds.) *Interpretability Issues in Fuzzy Modeling*, pp. 278–302. Springer, Berlin (2003)
394. Setnes, M., Babuska, R., Kaymak, U., Lemke, H.: Similarity measures in fuzzy rule base simplification. *IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics* 28(3), 376–386 (1998)
395. Sherman, J., Morrison, W.: Adjustment of an inverse matrix corresponding to changes in the elements of a given column or a given row of the original matrix. *Annals of Mathematical Statistics* 20, 621 (1949)
396. Shi, J., Malik, J.: Normalized cuts and image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 22(8), 888–905 (2000)
397. Siler, W., Buckley, J.: *Fuzzy Expert Systems and Fuzzy Reasoning: Theory and Applications*. John Wiley & Sons, Chichester (2005)
398. Silva, L., Gomide, F., Yager, R.: Participatory learning in fuzzy clustering. In: IEEE International Conference on Fuzzy Systems, FUZZ-IEEE 2005, Reno, Nevada, pp. 857–861 (2005)
399. Simani, S., Fantuzzi, C., Patton, R.: *Model-based Fault Diagnosis in Dynamic Systems Using Identification Techniques*. Springer, Heidelberg (2002)
400. Simoudis, E., Aha, D.: Special issue on lazy learning. *Artificial Intelligence Review* 11(1-5) (1997)
401. Smith, J., Tahir, M.: Stop wasting time: On predicting the success or failure of learning for industrial applications. In: Yin, H., Tino, P., Corchado, E., Byrne, W., Yao, X. (eds.) IDEAL 2007. LNCS, vol. 4881, pp. 673–683. Springer, Heidelberg (2007)
402. Smith, L.I.: A tutorial on principal component analysis (2002), http://www.cs.otago.ac.nz/cosc453/student_tutorials/principal_components.pdf

403. Smithson, M.: Confidence Intervals. SAGE University Paper (Series: Quantitative Applications in the Social Sciences), Thousand Oaks, California (2003)
404. So, C., Ng, S., Leung, S.: Gradient based variable forgetting factor RLS algorithm. *Signal Processing* 83(6), 1163–1175 (2003)
405. Sobue, S., Huang, X., Chen, Y.: Mapping functions between image features and KANSEI and its application to KANSAI based clothing fabric image retrieval. In: Proceedings of the 23rd International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC 2008), Yamaguchi, Japan, pp. 705–708 (2008)
406. Song, M., Wang, H.: Incremental estimation of gaussian mixture models for online data stream clustering. In: Proceedings of the International Conference on Bioinformatics and its Applications, Fort Lauderdale, Florida, USA (2004)
407. Song, Q.: Adaptive evolving neuro-fuzzy systems for dynamic system identification. Ph.D. thesis. University of Otago, New Zealand (2002)
408. Stephani, H., Hermann, M., Wiesauer, K., Katletz, S., Heise, B.: Enhancing the interpretability of thz data through unsupervised classification. In: Proc. of the IMEKO XIX World Congress, Fundamental and Applied Metrology, Lisbon, Portugal (2009)
409. Stockman, G., Shapiro, L.: Computer Vision. Prentice Hall, Upper Saddle River (2001)
410. Stone, M.: The generalized weierstrass approximation theorem. *Mathematics Magazine* 29(4), 167–184 (1948)
411. Stone, M.: Cross-validators choice and assessment of statistical predictions. *Journal of the Royal Statistical Society* 36(1), 111–147 (1974)
412. Sugeno, M.: Industrial Applications of Fuzzy Control. Elsevier Science, Amsterdam (1985)
413. Sutton, R., Barto, A.: Reinforcement learning: an introduction. MIT Press, Cambridge (1998)
414. Swanson, D.: Signal Processing for Intelligent Sensors. Marcel Dekker, New York (2000)
415. Swierenga, H., de Weier, A., van Wijk, R., Buydens, L.: Strategy for constructing robust multivariate calibration models. *Chemometrics and Intelligent Laboratory Systems* 49(1), 1–17 (1999)
416. Tahir, M.A., Smith, J.: Improving nearest neighbor classifier using tabu search and ensemble distance metrics. In: Proceedings of the Eleventh International Conference on Machine Learning
417. Takagi, T., Sugeno, M.: Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions on Systems, Man and Cybernetics* 15(1), 116–132 (1985)
418. Thompson, C., Califf, M., Mooney, R.: Active learning for natural language parsing and information extraction. In: Proceedings of 16th International Conference on Machine Learning, Bled, Slovenia, pp. 406–414 (1999)
419. Thumfart, S., Jacobs, R., Lughofer, E., Cornelissen, F., Maak, H., Groissboeck, W., Richter, R.: Modelling human aesthetic perception of visual textures. *ACM Transactions on Applied Perception* (to appear, 2010)
420. Thumfart, S., Jacobs, R.H., Haak, K.V., Cornelissen, F.W., Scharinger, J., Eitzinger, C.: Feature based prediction of perceived and aesthetic properties of visual textures. In: Proc. Materials & Sensations 2008, PAU, France, pp. 55–58 (2008)
421. Tick, J., Fodor, J.: Fuzzy implications and inference processes. *Computing and Informatics* 24(6), 591–602 (2005)
422. Tickle, A., Andrews, R., Golea, M., Diederich, J.: The truth will come to light: directions and challenges in extracting the knowledge embedded within the trained artificial neural networks. *IEEE Transactions on Neural Networks* 9(6), 1057–1068 (1998)

423. Tikhonov, A., Arsenin, V.: Solutions of ill-posed problems. Winston & Sons, Washington D.C. (1977)
424. Tikhonov, A., Glasko, V.: Use of the regularization method in non-linear problems. U.S.S.R. Computational Mathematics and Mathematical Physics 5(3), 93–107 (1965)
425. Tong, R., Beck, M., Latten, A.: Fuzzy control of the activated sludge wastewater treatment process. Automatica 16(6), 695–701 (1980)
426. Tong, S., Koller, D.: Support vector machine active learning with application to text classification. Journal of Machine Learning Research 2, 45–66 (2001)
427. Treado, P., Levin, I., Lewis, E.: Near-infrared acousto-optic filtered spectroscopic microscopy: A solid-state approach to chemical imaging. Applied Spectroscopy 46(4), 553–559 (1992)
428. Tschumitschew, K., Klawonn, F.: Incremental quantile estimation. Evolving Systems (in press, 2010), doi:10.1007/s12530-010-9017-7
429. Tsymbal, A.: The problem of concept drift: definitions and related work. Tech. Rep. TCD-CS-2004-15, Department of Computer Science, Trinity College Dublin, Ireland (2004)
430. Turban, E., Aronson, J., Liang, T.P.: Decision Support Systems and Intelligent Systems, 7th edn. Prentice Hall, Upper Saddle River (2004)
431. Utgoff, P.: Incremental induction of decision trees. Machine Learning 4(2), 161–186 (1989)
432. Vaira, S., Mantovani, V.E., Robles, J., Sanchis, J.C., Goicoechea, H.: Use of chemometrics: Principal component analysis (PCA) and principal component regression (PCR) for the authentication of orange juice. Analytical Letters 32(15), 3131–3141 (1999)
433. Vandeginste, B., Massart, D., Buydens, L., Jong, S.D., Lewi, P., Smeyer-Verbeke, J.: Handbook of Chemometrics and Qualimetrics Part B. Elsevier, Amsterdam (1998)
434. Vapnik, V.: Statistical Learning Theory. Wiley and Sons, New York (1998)
435. Wang, H., Fan, W., Yu, P., Han, J.: Mining concept-drifting data streams using ensemble classifiers. In: Proceedings of the 9th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, New York, USA, pp. 226–235 (2003)
436. Wang, J., Yu, B., Gasser, L.: Classification visualization with shaded similarity matrices. Tech. rep., Graduate school of Library and Information Science, UIUC (2002)
437. Wang, J.H., Sun, W.D.: Online learning vector quantization: a harmonic competition approach based on conservation network. IEEE Transactions on Systems, Man, and Cybernetics, part B: Cybernetics 29(5), 642–653 (1999)
438. Wang, L.: Fuzzy systems are universal approximators. In: Proc. 1st IEEE Conf. Fuzzy Systems, San Diego, CA, pp. 1163–1169 (1992)
439. Wang, L., Mendel, J.: Fuzzy basis functions, universal approximation and orthogonal least-squares learning. IEEE Transactions on Neural Networks 3(5), 807–814 (1992)
440. Wang, L., Yen, J.: Extracting fuzzy rules for system modelling using a hybrid of genetic algorithm and Kalman filter. Fuzzy Sets and Systems 101(3), 353–362 (1999)
441. Wang, W., Vrbanek, J.: An evolving fuzzy predictor for industrial applications. IEEE Transactions on Fuzzy Systems 16(6), 1439–1449 (2008)
442. Wang, X., Kruger, U., Lennox, B.: Recursive partial least squares algorithms for monitoring complex industrial processes. Control-Engineering-Practice 11(6), 613–632 (2003)
443. Ware, M., Frank, E., Holmes, G., Hall, M., Witten, I.: Interactive machine learning: letting users build classifiers. International Journal of Human-Computer Studies 55(3), 281–292 (2001)
444. Wasserman, P.: Advanced Methods in Neural Computing. Van Nostrand Reinhold, New York (1993)

445. Wei, L.Y., Levoy, M.: Fast texture synthesis using tree-structured vector quantization. In: Proceedings of the 27th Annual Conference on Computer Graphics and Interactive Techniques (SIGGRAPH), New York, pp. 479–488 (2000)
446. Werbos, P.: Beyond regression: New tools for prediction and analysis in the behavioral sciences. Ph.D. thesis, Appl. Math., Harvard University, USA (1974)
447. Widmer, G., Kubat, M.: Learning in the presence of concept drift and hidden contexts. *Machine Learning* 23(1), 69–101 (1996)
448. Wolpert, D.: No free lunch theorems for optimization. *IEEE Transactions on Evolutionary Computation* 1(1), 67–82 (1997)
449. Wu, S., Er, M., Gao, Y.: A fast approach for automatic generation of fuzzy rules by generalized dynamic fuzzy neural networks. *IEEE Transactions on Fuzzy Systems* 9(4), 578–594 (2001)
450. Wu, S., Er, M.J.: Dynamic fuzzy neural networks - a novel approach to function approximation. *IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics* 30(2), 358–364 (2000)
451. Wu, X., Kumar, V., Quinlan, J., Gosh, J., Yang, Q., Motoda, H., MacLachlan, G., Ng, A., Liu, B., Yu, P., Zhou, Z.H., Steinbach, M., Hand, D., Steinberg, D.: Top 10 algorithms in data mining. *Knowledge and Information Systems* 14(1), 1–37 (2006)
452. Xiaoan, W., Bellgardt, K.H.: On-line fault detection of flow-injection analysis systems based on recursive parameter estimation. *Analytica Chimica Acta* 313(3), 161–176 (1995)
453. Xu, L., Schuurmans, D.: Unsupervised and semi-supervised multi-class support vector machines. In: Proceedings of the 20th National Conference on Artificial Intelligence (AAAI 2005), Pittsburgh, Pennsylvania, pp. 904–910 (2005)
454. Yager, R., Filev, D.: Learning of fuzzy rules by mountain clustering. In: Proceedings of the SPIE Conference on Application of Fuzzy Logic Technology, Boston, MA, pp. 246–254 (1993)
455. Yager, R., Filev, D.: Approximate clustering via the mountain method. *IEEE Transactions on Systems, Man and Cybernetics* 24(8), 1279–1284 (1994)
456. Yager, R.R.: A model of participatory learning. *IEEE Transactions on Systems, Man and Cybernetics* 20(5), 1229–1234 (1990)
457. Yan, W., Shao, H., Wang, X.: Soft sensing modelling based on support vector machine and bayesian model selection. *Computers and Chemical Engineering* 28(8), 1489–1498 (2004)
458. Yang, M., Wu, K.: A new validity index for fuzzy clustering. In: Proceedings of the IEEE International Conference on Fuzzy Systems, Melbourne, Australia, pp. 89–92 (2001)
459. Ye, J., Li, Q., Xiong, H., Park, H., Janardan, R., Kumar, V.: IDR, QR: An incremental dimension reduction algorithms via QR decomposition. *IEEE Transactions on Knowledge and Data Engineering* 17(9), 1208–1222 (2005)
460. Yen, J., Wang, L.: Application of statistical information criteria for optimal fuzzy model construction. *IEEE Transactions on Fuzzy Systems* 6(3), 362–372 (1998)
461. Yen, J., Wang, L.: Simplifying fuzzy rule-based models using orthogonal transformation methods. *IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics* 29(1), 13–24 (1999)
462. Yen, J., Wang, L., Gillespie, C.: Improving the interpretability of TSK fuzzy models by combining global learning and local learning. *IEEE Transactions on Fuzzy Systems* 6(4), 530–537 (1998)
463. Yeung, K., Ruzzo, W.: Principal component analysis for clustering gene expression data. *Bioinformatics* 17(9), 763–774 (2001)

464. Zadeh, L.: Fuzzy sets. *Information and Control* 8(3), 338–353 (1965)
465. Zadeh, L.: Outline of a new approach to the analysis of complex systems and decision processes. *IEEE Transactions Systems, Man and Cybernetics* 3, 28–44 (1973)
466. Zadeh, L.: The concept of a linguistic variable and its application to approximate reasoning. *Information Sciences* 8(3), 199–249 (1975)
467. Zadeh, L.: Fuzzy sets and information granularity. In: *Advances in Fuzzy Set Theory and Applications*, pp. 3–18 (1979)
468. Zhang, Y.Q.: Constructive granular systems with universal approximation and fast knowledge discovery. *IEEE Transactions on Fuzzy Systems* 13(1), 48–57 (2005)
469. Zhou, S., Gan, J.: Low-level interpretability and high-level interpretability: a unified view of data-driven interpretable fuzzy systems modelling. *Fuzzy Sets and Systems* 159(23), 3091–3131 (2008)
470. Zhou, X., Angelov, P.: Real-time joint landmark recognition and classifier generation by an evolving fuzzy system. In: *Proceedings of FUZZ-IEEE 2006, Vancouver, Canada*, pp. 1205–1212 (2006)
471. Zhou, X., Angelov, P.: Autonomous visual self-localization in completely unknown environment using evolving fuzzy rule-based classifier. In: *2007 IEEE International Conference on Computational Intelligence Application for Defense and Security, Honolulu, Hawaii, USA*, pp. 131–138 (2007)
472. Zhu, X.: Semi-supervised learning literature survey. Tech. Rep. TR 1530, Computer Sciences, University of Wisconsin - Madison, Wisconsin, U.S.A. (2008)
473. Zoelzer, U.: *Digital Audio Signal Processing*. John Wiley & Sons, Chichester (2008)

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