APEM journal
Advances in Production Engineering & Management
Volume 12 | Number 4 | December 2017 | pp 321–336
https://doi.org/10.14743/apem2017.4.261
ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

An integrated generalized discriminant analysis method and chemical reaction support vector machine model (GDA-CRSVM) for bearing fault diagnosis

Nguyen, V.H.[a,b,c,*], **Cheng, J.S.**[a,b], **Thai, V.T.**[a,b,c]

[a]State Key Laboratory of Advanced Design and Manufacturing for Vehicle Body, Hunan University, Changsha, China
[b]College of Mechanical and Vehicle Engineering, Hunan University, Changsha, China
[c]Mechanical Engineering Department, Hanoi University of Industry, Hanoi, Vietnam

ABSTRACT

An expert technique in bearing fault diagnosis is proposed for the identification of actual status. A new diagnosis method based on a two-stage hybrid modality in integrating generalized discriminant analysis (GDA) with the chemical reaction support vector machine (CRSVM) classification model, named GDA-CRSVM, is proposed. The GDA reduces high-dimensional data to a more compact data, which serves an optimized CRSVM classification model with input data, in which a support vector machine (SVM) classifier model with the best parameters are selected by the meta-heuristic chemical reaction optimization algorithm (CRO) to build an optimized CRSVM classification model. The implementation of the new proposed method is based on a multi-aspect feature (MAF) set that presents most of the actual aspects of the complex vibration signal. The MAF set is collected from the statistical features in time-domain, frequency-domain, and time-frequency domain features are extracted by local characteristic-scale decomposition (LCD). Experiments have been conducted on two bearing vibration datasets by the expert technique in the bearing fault diagnosis. Results shown that the effectiveness of GDA-CRSVM in terms of classification accuracy and execution time.

ARTICLE INFO

Keywords:
Bearing fault
Expert fault diagnosis technique
Chemical reaction support vector machine (CRSVM)
Multi-aspect feature set
Generalized discriminant analysis (GDA)

**Corresponding author:*
hung2009haui@gmail.com
(Nguyen, V.H.)

Article history:
Received 8 June 2017
Revised 23 October 2017
Accepted 26 October 2017

References

[1] Zheng, J., Cheng, J., Yang, Y (2013). A rolling bearing fault diagnosis approach based on LCD and fuzzy entropy, *Mechanism and Machine Theory,* Vol. 70, 441-453, doi: 10.1016/j.mechmachtheory.2013.08.014.
[2] Liu, H., Wang, X., Lu, C. (2015). Rolling bearing fault diagnosis based on LCD–TEO and multifractal detrended fluctuation analysis, *Mechanical Systems and Signal Processing,* Vol. 60-61, 273-288, doi: 10.1016/j.ymssp.2015.02.002.
[3] Chen, J., Liao, C.-M. (2002). Dynamic process fault monitoring based on neural network and PCA, *Journal of Process Control,* Vol. 12, No. 2, 277-289, doi: 10.1016/S0959-1524(01)00027-0.
[4] Jolliffe, I.T. (2010). *Principal Component Analysis, Second Edition,* Springer, New York, USA.
[5] Cox, T.F., Cox, M.A.A. (1994). *Multidimensional Scaling, Second Edition,* Chapman & Hall, London, UK.
[6] Martinez, A.M., Kak, A.C. (2001). PCA versus LDA, *IEEE Transactions on Pattern Analysis and Machine Intelligence,* Vol. 23, No. 2, 228-233, doi: 10.1109/34.908974.
[7] Belhumeur, P.N., Hespanha, J.P., Kriegman, D.J. (1997). Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection, *IEEE Transactions on Pattern Analysis and Machine Intelligence,* Vol. 19, No. 7, 711-720, doi: 10.1109/34.598228.
[8] Baudat, G., Anouar, F. (2000). Generalized discriminant analysis using a kernel approach, *Neural Computation,* Vol. 12, No. 10, 2385-2404, doi: 10.1162/089976600300014980.

[9] Dogantekin, E., Dogantekin, A., Avci, D. (2011). An expert system based on generalized discriminant analysis and wavelet support vector machine for diagnosis of thyroid diseases, *Expert Systems with Applications,* Vol. 38, No. 1, 146-150, doi: 10.1016/j.eswa.2010.06.029.

[10] Li, C.-H., Kuo, B.-C., Lin, L.-H., Wu, W., Lan, D. (2013). Apply an automatic parameter selection method to generalized discriminant analysis with RBF kernel for hyperspectral image classification, In: *2013 International Conference on Machine Learning and Cybernetics*, Tianjin, China, 253-258, doi: 10.1109/ICMLC.2013.6890477.

[11] Abbasion, S., Rafsanjani, A., Farshidianfar, A., Irani, N. (2007). Rolling element bearings multi-fault classification based on the wavelet denoising and support vector machine, *Mechanical Systems and Signal Processing,* Vol. 21, No. 7, 2933-2945, doi: 10.1016/j.ymssp.2007.02.003.

[12] Lau, K.W., Wu, Q.H. (2008). Local prediction of non-linear time series using support vector regression, *Pattern Recognition,* Vol. 41, No. 5, 1539-1547, doi: 10.1016/j.patcog.2007.08.013.

[13] Pelossof, R., Miller, A., Allen, P., Jebara, T. (2004). An SVM learning approach to robotic grasping, In: *2004 IEEE International Conference on Robotics and Automation, 2004, Proceedings. ICRA '04.*, Vol. 4, 3512-3518, doi: 10.1109/ROBOT.2004.1308797.

[14] Gryllias, K.C., Antoniadis, I.A. (2012). A support vector machine approach based on physical model training for rolling element bearing fault detection in industrial environments, *Engineering Applications of Artificial Intelligence,* Vol. 25, No. 2, 326-344, doi: 10.1016/j.engappai.2011.09.010.

[15] Samanta, B. (2004). Gear fault detection using artificial neural networks and support vector machines with genetic algorithms, *Mechanical Systems and Signal Processing,* Vol. 18, No. 3, 625-644, doi: 10.1016/S0888-3270(03)00020-7.

[16] Dou, D., Zhou, S. (2016). Comparison of four direct classification methods for intelligent fault diagnosis of rotating machinery, *Applied Soft Computing,* Vol. 46, 459-468, doi: 10.1016/j.asoc.2016.05.015.

[17] Zhang, X., Chen, W., Wang, B., Chen, X. (2015). Intelligent fault diagnosis of rotating machinery using support vector machine with ant colony algorithm for synchronous feature selection and parameter optimization, *Neurocomputing,* Vol. 167, 260-279, doi: 10.1016/j.neucom.2015.04.069.

[18] Gomes, T.A.F., Prudêncio, R.B.C., Soares, C., Rossi, A.L.D., Carvalho, A. (2012). Combining meta-learning and search techniques to select parameters for support vector machines, *Neurocomputing,* Vol. 75, No. 1, 3-13, doi: 10.1016/j.neucom.2011.07.005.

[19] Yang, D., Liu, Y., Li, S., Li, X., Ma, L. (2015). Gear fault diagnosis based on support vector machine optimized by artificial bee colony algorithm, *Mechanism and Machine Theory,* Vol. 90, 219-229, doi: 10.1016/j. mechmachtheory.2015.03.013.

[20] Lam, A.Y.S., Li, V.O.K. (2010). Chemical-Reaction-Inspired Metaheuristic for Optimization, *IEEE Transactions on Evolutionary Computation,* Vol. 14, No. 3, 381-399, doi: 10.1109/TEVC.2009.2033580.

[21] Alatas, B. (2012). A novel chemistry based metaheuristic optimization method for mining of classification rules, *Expert Systems with Applications,* Vol. 39, No. 2, 11080-11088, doi: 10.1016/j.eswa.2012.03.066.

[22] Li, J.-Q., Pan, Q.-K. (2013). Chemical-reaction optimization for solving fuzzy job-shop scheduling problem with flexible maintenance activities, *International Journal of Production Economics,* Vol. 145, No. 1, 4-17, doi: 10.1016/j.ijpe.2012.11.005.

[23] Lam, A.Y.S., Li, V.O.K. (2012). Chemical reaction optimization: A tutorial, *Memetic Computing*, Vol. 4, No. 1, 3-17, doi: 10.1007/s12293-012-0075-1.

[24] Vapnik, V.N. (1995). *The Nature of Statistical Learning Theory*, Springer, New York, USA, doi: 10.1007/978-1-4757-2440-0.

[25] Yu, Y., YuDejie, Junsheng, C. (2006). A roller bearing fault diagnosis method based on EMD energy entropy and ANN, *Journal of Sound and Vibration,* Vol. 294, No. 1-2, 269-277, doi: 10.1016/j.jsv.2005.11.002.