Abstract

Hyperspectral image Classification is one of the most active areas of research and development in the field of hyperspectral image analysis. Recently, many approaches have been extensively studied to improve the classification performance, in which integrating the spectral and the spatial information contained in the original hyperspectral image data is a simple and effective way. In this paper, A novel spectral-spatial Hyperspectral image classification method is proposed, which extract spatial feature before classification by principle component analysis (PCA)/Randomized Singular Value Decomposition (RSVD). The 3-dimensional discrete wavelet transform (3D-DWT) is applied to extract the spatial feature. The local spatial correlation of neighboring pixels is modeled using Markov random field (MRF) based on the probabilistic classification map obtained by applying probabilistic support vector machine (SVM)/Multinomial Logistic Regression (MLRsub) to the extracted 3D-DWT features, and then a maximum posterior (MAP) classification problem can be formulated in a Bayesian perspective. α-Expansion min-cut-based optimization algorithm is used to solve this MAP problem efficiently. Experimental results on two benchmark HSIs show that the RSVD-3D-DWT based on methods
give better performance than PCA-3D-DWT and 3D-DWT [1] based on methods gain beyond state-of-the-art methods.

References

1. Cao, X., Xu, L., Meng, D., Zhao, Q., and Xu, Z., 2016 “Integration of 3-dimensional discrete wavelet transform and Markov random field for hyperspectral image classification”, Neurocomputing journal, [http://dx.doi.org/10.1016/j.neucom.2016.11.034]
2. El-Rahman, S. A., Aliady, W. A., and Alrashed, N. I. 2015, ”Supervised Classification Approaches to Analyze Hyperspectral Dataset”, I. J. Image, Graphics and Signal Processing, pages 42–48.
3. Jensen, R., 2005, “Introductory digital image processing”, Pearson Prentice Hall.
4. Plaza, A., Martinez, P., Perez, R. and Plaza, J., 2004, ”A new approach to mixed pixel classification of hyperspectral imagery based on extended morphological profiles”, Pattern Recognition, 37, 1097–1116.
5. Benediktsson, J.A., Palmason, J.A. and Sveinsson, J.R, 2005, “Classification of hyperspectral data from urban areas based on extended morphological profiles”, IEEE Trans. Geo-science Remote Sens. 43, 480–491.
6. Ghamisi, P., Dalla Mura, M., Benediktsson, J.A, 2015. “A survey on spectral–spatial classification techniques based on attribute profiles”, IEEE Trans. Geo-science Remote Sens. 53, 2335–2353.
7. Tuia, D., Volpi, M., Dalla Mura, M., Rakotomamonjy, A. and Flamary, R., 2014. “Automatic feature learning for spatio-spectral image classification with sparse SVM”, IEEE Trans. Geo-science. Remote Sens. 52, 6062–6074.
8. Dalla Mura, M., Villa, A., Benediktsson, J.A., Chanussot, J. and Bruzzone, L, 2011. ”Classification of hyperspectral images by using extended morphological attribute profile sand independent component analysis”, IEEE Geo-science Remote Sens. Letter 8, 542–546.
9. Jia, S., Zhang, X. and Li, Q., 2015. “Spectral–spatial hyperspectral image classification using regularized low-rank representation and sparse representation-based graph cuts”, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 8, 2473–2484.
10. Zhang, X., Xu, C., Li, M. and Sun, X, 2015. “Sparse and Low-rank coupling image segmentation model via non-convex regularization”, Int. J. Pattern Recognition Artificial Intelligence.
11. Zhang, B., Li, S., Jia, X., Gao, L. and Peng, M., 2011. “Adaptive Markov Random field approach for classification of hyperspectral imagery”. IEEE Geoscience Remote Sens. Letter, 8, 973–977.
12. Tarabalka, Y. and Rana, A., 2014. “ Graph-cut-based model for spectral-spatial classification of hyperspectral images”, In Proceedings of the 2014 IEEE Geoscience and Remote Sensing Symposium, Quebec, QC, Canada, 13–18, pp. 3418–3421.
13. Pajares, G., Lópezmartínez, C., Sánchezlladó, F.J. and Molina, I., 2012. “Improving Wishart classification of polarimetric SAR data using the Hopfield neural network optimization approach”. Remote Sens. 4, 3571–3595.
14. Guijarro, M., Pajares, G. and Herrera, P.J., 2009. “Image-based airborne sensors: A combined approach for spectral signatures classification through deterministic simulated annealing”, Sensors,9, 7132–7149.
15. Sánchez-Lladó, F.J., Pajares, G. and López-Martínez, C., 2011. “Improving the Wishart
synthetic aperture radar image classifications through deterministic simulated annealing”, ISPRS J. Photogramm. Remote Sens. 66, 845–857.

16. Zhong, Y., Ma, A. and Zhang, L., 2014. “An adaptive Memetic fuzzy clustering algorithm with spatial information for remote sensing imagery”. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., 7, 1235–1248.

17. Qian, Y., Ye, M. and Zhou, J., 2013. “Hyperspectral image classification based on structured sparse logistic regression and three-dimensional wavelet texture features”, IEEE Trans. Geo-science Remote Sens., 51, 2276–2291.

18. Shen, L. and Jia, S., 2011. “Three-dimensional Gabor wavelets for pixel-based hyperspectral imagery classification” IEEE Trans. Geo-science Remote Sens., 49, 5039–5046.

19. Tang, Y., Lu, Y. and Yuan, H., 2015. “Hyperspectral image classification based on three-dimensional scattering wavelet transform”, IEEE Trans. Geoscience Remote Sens., 53, 2467–2480.

20. Zhang, L., Zhang, L., Tao, D. and Huang, X., 2013 “Tensor discriminative locality alignment for hyperspectral image spectral–spatial feature extraction”, IEEE Trans. Geoscience Remote Sens., 53, 242–256.

21. Zhang, L., Zhang, Q., Zhang, L., Tao, D., Huang, X. and Du, B., 2015. “Ensemble manifold regularized sparse low-rank approximation for multiview feature embedding”, Pattern Recognition, 48, 3102–3112.

22. Melgani, F., and Bruzzone, L., 2004. “Classification of hyperspectral remote sensing images with support vector machines,” IEEE Trans. Geosci. Remote Sens., vol. 42, no. 8, pp. 1778–1790.

23. Chen, Y., Nasrabadi, N. M. and Tran, T. D., 2011. “Simultaneous joint sparsity model for target detection in hyperspectral imagery,” IEEE Geo-science. Remote Sens. Letter, vol. 8, no. 4, pp. 676–680.

24. Chen, Y., Nasrabadi, N. M. and Tran, T. D., 2011. “Hyperspectral image classification using dictionary based sparse representation”, IEEE Trans. Geo-science. Remote Sens., vol. 49, no. 10, pp. 3973–3985.

25. Li, J., Bioucas-Dias, J. M. and Plaza, A., 2012. “Spectral-spatial hyperspectral image segmentation using subspace multinomial logistic regression and Markov random field,” IEEE Trans. Geoscience Remote Sens., vol. 50, no. 3, pp. 809–823.

26. Camps-Valls, G., Gomez-Chova, L., Muñoz-Mari, J., Vila-Francés, J. and CalpeMaravilla, J., 2006. “Composite kernels for hyperspectral image classification”, IEEE Geoscience and Remote Sensing Letters 3 (1) , 93–97.

27. Gu, Y., Wang, Q., Wang, H., You, D. and Zhang, Y., 2015. “Multiple kernel learning via low-rank nonnegative matrix factorization for classification of hyperspectral imagery”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 8 (6), 2739–2751.

28. Böhning, D., 1992. “Multinomial logistic regression algorithm”, Annals of the Institute of Statistical Mathematics 44 (1) 197–200.

29. Qian, Y., Ye, M. and Zhou, J., 2013. “Hyperspectral image classification based on structured sparse logistic regression and three-dimensional wavelet texture features”, IEEE Transactions on Geoscience and Remote Sensing 51 (4), 2276–2291.

30. Zhao, W. and Du, S., 2016. “Spectral–spatial feature extraction for hyperspectral image classification: A dimension reduction and deep learning approach”, IEEE Trans. Geoscience Remote Sens., 54, 4544–4554.
31. Yue, J., Zhao, W., Mao, S. and Liu, H., 2015. “Spectral-spatial classification of hyperspectral images using deep convolutional neural networks”. Remote Sens. Letter, 6, 468–477.

32. Makantasis, K., Karantzalos, K., Doulamis,A., Doulamis,N., 2015. “Deep supervised learning for hyperspectral data classification through convolutional neural networks”. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, Milan, Italy, 26–31, pp. 4959–4962.

33. Liang, H. and Li, Q., 2016. “Hyperspectral imagery classification using sparse representations of convolutional neural network features”. Remote Sens., 8.

34. Martinsson P.G. and Voronin S., 2015. "A Randomized blocked Algorithm for Efficiently Computing Rank-Revealing Factorizations of Matrices.", arXiv preprint, pp. 1-26.

35. Erichson N. B., Voronin, S., Brunton S. L., Kutz J. N., 2017. " Randomized Matrix Decompositions using R", Journal of Statistical Software, arXiv:1608.02148v3, 3.

36. Chun-Lin, L., 2010. “A tutorial of the wavelet transform”, NTUEE, Taiwan.

37. Vapnik, V. and Chervonenkis, A., 1991. “The necessary and sufficient conditions for consistency in the empirical risk minimization method", Pattern Recognition and Image Analysis, 1(3):283–305.

38. Camps-Valls, G. and Bruzzone, L., 2005. "Kernel-based methods for hyperspectral image classification", IEEE Transactions on Geoscience and Remote Sensing, 43(6):1351–1362.

39. Wu, T.-F., Lin, C.-J. and Weng, R. C., 2004. “Probability estimates for multi-class classification by pairwise coupling”. Journal of Machine Learning Research, 5:975–1005.

40. Lin, C.-J., Lin, H.-T. and Weng, R. C., 2003. “A note on Platt’s probabilistic outputs for support vector machines", Department of Computer Science, National Taiwan University, Taipei, Taiwan.

41. Chang, C. and Lin, C., 2009. “LIBSVM: A library for support vector machines".

42. Clifford, P., 1990. “ Markov random fields in statistics", In Geoffrey Grimmett and Dominic Welsh, editors, Disorder in Physical Systems: A Volume in Honour of John M. Hammersley, pages 19–32. Oxford University Press, Oxford.

43. Richards, J. A. and Jia, X., 2006. " Remote Sensing Digital Image Analysis", Springer-Verlag Berlin Heidelberg, 4th edition.

Index Terms

Computer Science  Image Processing

Keywords
Spectral-Spatial Hyperspectral Image Classification based on Randomized Singular Value Decomposition (RSVD), Principle Component Analysis (PCA), Randomized Singular Value Decomposition (RSVD), 3-Dimensional Discrete Wavelet Transform (3D-DWT), Support Vector Machine (SVM), Multinomial Logistic Regression (MLR), and Markov Random Field (MRF).