Maximum auto-mutual-information factor analysis

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ABSTRACT

Based on the information theoretical measure mutual information derived from entropy and Kullback-Leibler divergence, an alternative to maximum autocorrelation factor analysis is sketched.

1. INTRODUCTION

In signal and image processing principal component analysis[1] (PCA) is often used for dimensionality reduction and feature extraction in pre-processing steps to for example classification.

In remote sensing image analysis PCA is often replaced by maximum autocorrelation factor[2] (MAF) or minimum noise fraction[3] (MNF) analysis. This is done because MAF and MNF analyses incorporate spatial information in the orthogonalization of the multivariate data which is conceptually more satisfactory and which typically gives better results.

In this contribution, autocorrelation between the multivariate data and a spatially shifted version of the same data in the MAF analysis is replaced by the information theoretical, entropy and Kullback-Leibler divergence based measure mutual information.[4–8] This potentially gives a more detailed decomposition of the data. Also, the orthogonality between already found components and components of higher order requested in the MAF analysis is replaced by a requirement of minimum mutual information between components. These ideas resulting in maximum auto-mutual-information factor analysis are in turn based on.[9–11]

The sketched methods are used on the well-known AVIRIS*[12] Indian Pines data.

REFERENCES

[1] Hotelling, H., "Analysis of a complex of statistical variables into principal components," *Journal of Educational Psychology* **24**, 417–441 (1933).

[2] Switzer, P. and Green, A. A., "Min/max autocorrelation factors for multivariate spatial imagery," Tech. Rep. 6, Department of Statistics, Stanford University (1984).

[3] Green, A. A., Berman, M., Switzer, P., and Craig, M. D., "A transformation for ordering multispectral data in terms of image quality with implications for noise removal," *IEEE Transactions on Geoscience and Remote Sensing* **26**, 65–74 (Jan. 1988).

[4] Shannon, C. E., "A mathematical theory of communication," *Bell System Technical Journal* **27**(3), 379–423 and 623–656 (1948).

[5] Hyvärinen, A., Karhunen, J., and Oja, E., *Independent Component Analysis*, J. Wiley (2001).

[6] Mackay, D. J. C., *Information Theory, Inference and Learning Algorithms*, Cambridge University Press (2003).

[7] Bishop, C. M., *Pattern Recognition and Machine Learning*, Springer (2007).

[8] Canty, M. J., *Image Analysis, Classification and Change Detection in Remote Sensing. With Algorithms for ENVI/IDL and Python*, Taylor & Francis, CRC Press, third ed. (2014).

[9] Yin, X., "Canonical correlation analysis based on information theory," *Journal of Multivariate Analysis* **91**, 161–176 (2004).

*https://aviris.jpl.nasa.gov/

[10] Karasuyama, M. and Sugiyama, M., "Canonical dependency analysis based on squared-loss mutual information," *Neural Networks* **34**, 46–55 (2012).

[11] Vestergaard, J. S. and Nielsen, A. A., "Canonical information analysis," *ISPRS Journal of Photogrammetry and Remote Sensing* **101**, 1–9 (2015). http://www.imm.dtu.dk/pubdb/p.php?6270, Matlab code at https://github.com/schackv/cia.

[12] Vane, G., Green, R. O., Chrien, T. G., Enmark, H. T., Hansen, E. G., and Porter, W. M., "The airborne/infrared imaging spectrometer (AVIRIS)," *Remote Sensing of Environment* **44**, 127–143 (1993).