Analysis of Sub-Manifold Structure in Hyperspectral Imagery

[†]*Charles M. Bachmann,* [‡]*Thomas L. Ainsworth,* [†]*Robert A. Fusina*

Naval Research Laboratory
Remote Sensing Division
Coastal & Ocean Remote Sensing Branch
[†]Coastal Science & Interpretation Section, Code 7232
[‡]Image Sciences Section, Code 7263
4555 Overlook Ave., SW
Washington, D.C. 20375
Email: bachmann@nrl.navy.mil

1. INTRODUCTION

The physical reasons for the presence of nonlinearity in hyperspectral data are well known and have been described in a number of publications (see [14, 2, 3] and references therein). While many approaches to hyperspectral imagery analysis have relied on linear methods as an excellent first approximation, data driven methods that directly model this nonlinear structure are an important goal for many hyperspectral image applications where departures from linearity can influence the quality of derived products.

In several papers, we have previously developed a scalable methodology for parameterization of nonlinear structure in hyperspectral imagery (HSI) [2, 3]. There are many potential areas of application, including land-cover classification [3, 8], delineation of bathymetry and bottom type in water scenes [5, 6, 7, 9], and anomaly finding [5, 8]. A couple of our recent papers have focused on ways to further improve these representations by improving the manner in which the spectral neighborhood size is characterized and directly estimated from the data [1, 8]. In this paper, we focus on the local curvature and in particular the scale on which these changes occur, which is directly related to the notion of estimating the spectral neighborhood size.

2. SUB-MANIFOLD DESCRIPTIONS, NEIGHBORHOOD SIZE, AND INTRINSIC DIMENSIONALITY

It turns out that the scale on which neighborhood sizes tend to occur for particular classes appears to be an important additional dimensionality that is useful from the standpoint of class separation. Thus, we can use this scale as an important descriptor of particular classes of data, and this is the basis for an improved description of the data, one which is related to class separation. In particular, the scale of the neighborhood size can be quantified and added as an additional dimension in a feature space along with the manifold coordinate description which resulted from among other steps, the adaptive neighborhood estimation. Quantization of the neighborhood size occurs during the estimation procedure which we outlined in [8].

3. INTERCOMPARISONS IN HSI DATA

In order to explore this idea, we have used several different data sets from a number of different hyperspectral sensors, such as PROBE, HyMAP, PHILLS, CASI, and AVIRIS. In the presentation, we will describe how adding the additional feature dimension of neighborhood scale, derived from an adaptive neighborhood, can enhance the use of manifold coordinate representations of hyperspectral imagery. We draw illustrations from several applications areas such as land-cover classification, in water retrievals, and anomaly finding.

4. REFERENCES

[1] Ainsworth T. L., C. M. Bachmann, and R. A. Fusina, "Local Intrinsic Dimensionality from Non-linear Manifold Coordinates," Proc. IGARSS'07, 2007.

[2] Bachmann, C. M., T. L. Ainsworth, and R. A. Fusina, "Exploiting Manifold Geometry in Hyperspectral Imagery," *IEEE Trans. on Geoscience and Remote Sensing*, 43(3):441-454, 2005.

[3] Bachmann, C. M., T. L. Ainsworth, and R. A. Fusina, "Improved Manifold Coordinate Representations of Large Scale Hyperspectral Imagery," *IEEE Trans. Geosci. Rem. Sens.*, 44(10): 2786-2803, 2006.

[4] Bachmann, C. M., T. L. Ainsworth, and R. A. Fusina, "Classification Benchmarks for Full-Scene Manifold Coordinate Representations of Large-Scale Hyperspectral Scenes," Presentation at the International Geoscience & Remote Sensing Symposium IGARSS'06, Denver, Co., July/August 2006.

[5] Bachmann, C. M., T. L. Ainsworth, D. B. Gillis, S. J. Maness, M. J. Montes, T. F. Donato, J. H. Bowles, D. R. Korwan, R. A. Fusina, G. M. Lamela, and W. J. Rhea, "A New Data-Driven Approach to Modeling Coastal Bathymetry from Hyperspectral Imagery Using Manifold Coordinates," Proc. MTS/IEEE Oceans 2005 Conference, Washington, D.C., Sept. 2005.

[6] Bachmann, C. M., T. L. Ainsworth, D. B. Gillis, S. J. Maness, M. J. Montes, J. H. Bowles, D. R. Korwan, R. A. Fusina, T. F. Donato, G. M. Lamela, and W. J. Rhea, "Modeling Coastal Waters from Hyperspectral Imagery Using Manifold Coordinates," Proc. of the International Geoscience & Remote Sensing Symposium (IGARSS'06), Denver, Co., July/August 2006.

[7] C. M. Bachmann, T. L. Ainsworth, R. A. Fusina, M. J. Montes, J. H. Bowles, D. R. Korwan, "Bathymetric Retrieval from Manifold Coordinate Representations of Hyperspectral Imagery," Proc. IGARSS'07.

[8] C. M. Bachmann, T. L. Ainsworth, R. A. Fusina, "Automated Estimation of Spectral Neighborhood Size in Manifold Coordinate Representations of Hyperspectral Imagery: Implications for Anomaly Finding, Bathymetry Retrieval, and Land Applications," Proc. IGARSS'08.

[9] C. M. Bachmann, T. L. Ainsworth, R. A. Fusina, M. J. Montes, J. H. Bowles, D. R. Korwan, D. B. Gillis, "Bathymetric Retrieval from Hyperspectral Imagery Using Manifold Coordinate Representations," *IEEE Trans. on Geoscience and Remote Sensing*, in press.

[10] J. A. Costa, A. O. Hero, "Geodesic Entropic Graphs for Dimension and Entropy Estimation in Manifold Learning," IEEE Trans. Sig. Proc. 52(8): 2210-2221, 2004.

[11] J. A. Costa, A. O. Hero, "Manifold Learning Using Euclidean K-Nearest Neighbor Graphs," Proc. ICASSP, 2004.

[12] Y. Chen, M. M. Crawford, J. Ghosh, "Applying nonlinear manifold learning to hyperspectral data for land cover classification," Proc. IGARSS 2005, pp. 4311-4314.

[13] T. Han, D. Goodenough, "Nonlinear feature extraction of hyperspectral data based on local linear embedding (LLE)," in Proc. IGARSS 2005, pp. 1237-1240.

[14] C. D. Mobley, *Light and Water: Radiative Transfer in Natural Waters*.San Diego, CA: Academic, 1994.

[15] J. B. Tenenbaum, V. de Silva, J. C. Langford, 2000. "A global geometric framework for nonlinear dimensionality reduction," Science, 290(5500): 2319-2323.