ANOMALY DETECTION FOR HYPERSPECTRAL IMAGES USING LOCAL TANGENT SPACE ALIGNMENT

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1. INTRODUCTION

Anomaly detection is an important and challenging problem, which can potentially benefit from hyperspectral data. Greater availability of hyperspectral data over extended areas has increased the viability of its use in operational environments and stimulated increased research activity. Anomalies are spectrally different from their surroundings; generally, they are very small in spatial extent and have low probability of occurrence.

Dimensionality reduction (DR) is a useful preprocessing step for hyperspectral image data, both to reduce redundancy and improve performance. Although DR is lossy, it may improve separation between an anomaly and background signatures, resulting in improved detection [1]. Widely used linear DR methods such as principal component analysis (PCA) may not exploit the nonlinear properties that are often intrinsic in hyperspectral data [2]. Manifold learning addresses the problem of modeling nonlinear structures in the data by assuming that the original high dimensional data actually lie on a low dimensional manifold, and identifying coordinates that parameterize the data manifold. Manifold learning methods have been successfully applied to a variety of problems in hyperspectral image analysis [2]-[4].

Local tangent space alignment (LTSA) is a local manifold learning method, where the local geometry is described by the local tangent space of each data point [5]. We have previously applied it to hyperspectral image classification [6], and now investigate its effectiveness for anomaly detection. We propose to utilize the LTSA for DR, and then employ the minimum distance between a testing point and the global background in the embedded space for anomaly detection; our approach is denoted hereafter as LTSA-MD.

Applying LTSA to anomaly detection, problems of computational complexity and anomalous contamination must be addressed. The computational complexity of LTSA prevents its direct implementation for large images. Therefore, we choose a portion of points as training data to pass to the LTSA, and employ the kernel-based out-of-sample extension method to obtain the manifold coordinates for the whole image [6], [7]. For anomaly detection, the training data must represent all the background types in the image, but should not contain anomalies. Otherwise, detection performance deteriorates [8]. As an example, the popular kernel RX (KRX) detector [9] is impacted if the background covariance matrix estimated by training data contains anomalous information. Similarly, anomalies might contaminate the background manifold provided by LTSA, and thus affect anomaly detection. In this paper, the recursive hierarchical segmentation (RHSEG) algorithm [10] is applied to generate a much smaller number of spectral vectors (centroids of segments) to represent all the data. Moreover, the small segments that may represent the possible anomalies are removed, and the remaining segments are employed as training data to construct the background manifold.

2. METHODOLOGY

We employ the RHSEG method to generate background training data that are then utilized by LTSA to construct a reliable background manifold. Anomaly detection is achieved by measuring the separation of testing data and the background manifold. This LTSA-MD is applied according to the following implementation:

1: Select background training data via RHSEG.

2: Apply LTSA to the training data.

3: Employ the kernel-based out-of-sample extension for the whole image.

4: Calculate the minimum Euclidian distance between each point and background manifold.

RHSEG is a spatial-spectral image segmentation approach based on iterative hierarchical step-wise region growing [10]. In the implementation of RHSEG, merges are allowed only between spatially adjacent regions, which prevents the disjoint anomalies from merging. Consequently, potential anomalies can be removed by eliminating small segments, if the thresholding size parameter is assigned according to the size of desired anomalies. The remaining segments that represent reliable background are considered as training data. Additionally, we use Spectral Angle Mapper (SAM) as the distance metric in RHSEG, as it favors spectral shape over spectral magnitude, which is beneficial to hyperspectral data.

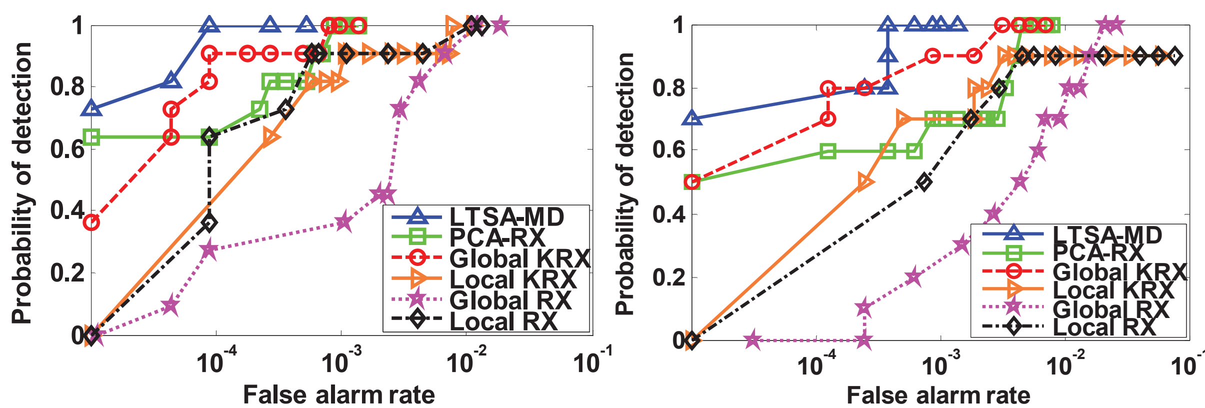
The LTSA-MD detector is adaptive to a background manifold with any shape, and has no assumption about data distribution. Moreover, the Euclidian distance on the manifold coordinates is equivalent to a nonlinear distance metric on the original data, which might improve the separation between anomalies and background.

3. EXPERIMENTAL RESUTLS

Two sets of hyperspectral data were utilized for experiments. The 242-band Hyperion data were acquired over an agricultural area of the state of Indiana, USA, in 2008. An area of 150×150 pixels was used for the experiments to illustrate the method. The interesting anomalies are a metal roof and storage silo. The 210-band HYDICE data were collected from an urban scene. The experimental data set is from a sub-image of 80×100 pixels, where two kinds of anomalies (car and roof) occurred.

3.1. Results of Anomaly Detection Experiments

Five other well-known anomaly detectors were applied to investigate the effectiveness of our algorithm. They were PCA DR followed by RX detection (PCA-RX), global KRX, local KRX, global RX and local RX, where dual windows (size of 5×5 and 15×15) were employed in the local methods, and the Gaussian radial basis function (RBF) kernel was used in the KRX detector with an experimentally selected value of *sigma.* It should be noted that the LTSA-MD and global KRX utilized the same background training data generated by RHSEG. The receiver operating characteristic (ROC) curve was employed for quantitative evaluation. Fig.1 (a) shows the ROC evaluation for Hyperion data: the LTSA-MD performed best with 2 false alarms under 100% probability of detection; both global KRX and PCA-RX achieved satisfactory results; local KRX and local RX yielded similar results; global RX resulted in the most interference. For HYDICE data, similar performances of the six approaches were observed, which are shown in Fig.1 (b). With our method, there were 3 false alarms under 100% probability of detection.



(a) (b)

Fig.1. ROC evaluation of different anomaly detectors: (a) Hyperion data, (b) HYDICE data.

3.2. Sensitivity Analysis of Parameters in LTSA-MD

Three free parameters were required for the LTSA-MD: the number of neighbors (k), the dimensionality of local tangent space (dL), and the dimensionality of global manifold (dG), where $k>dL$. Results from Hyperion and HYDICE data suggest: (1) For k and dL, the k value of 20 performed worst, while larger values of k (from 25 to 40) yielded similar good performance. Also, values of dL ranging from 15 to 30 achieved superior performance to dL=10. These indicate that the large values of k and dL are appropriate, and there is a large range for their selection. (2) For dG within the range of 8 to 12, the number of false alarms remained low, while outside that range (smaller or larger), the number increased. This suggests that dG is not difficult to choose, since the LTSA has good capability to distinguish anomalies from background using a small number of features.

4. CONCLUSIONS

This investigation of LTSA to anomaly detection in hyperspectral images indicated that the method is able to exploit the nonlinear properties of hyperspectral data and distinguish the anomalies from background. For these experiments, LTSA-MD outperformed the RX, PCA-RX, and KRX detectors. Additionally, anomaly detection using LTSA-MD was not sensitive to the number of neighbors and the dimensionality of local tangent space over a large range of values; the dimensionality of global manifold was also not difficult to choose since the first major features of LTSA have good separability. We can conclude from the experiments that the LTSA is an effective DR method for the application of anomaly detection in hyperspectral images.

5. REFERENCES

[1] B. Staab, "Investigation of noise and dimensionality reduction transforms on hyperspectral data as applied to target detection," May 2005, Available: http://www.cis.rit.edu/education/ugrad/ SeniorResearch /Staab-2005-bs.pdf.

[2] C. M. Bachmann and T. L. Ainsworth, "Exploiting manifold geometry in hyperspectral imagery," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 43, no. 3, pp. 441-454, Mar. 2005.

[3] T. Han and D. G. Goodenough, "Nonlinear feature extraction of hyperspectral data based on locally linear embedding," *IEEE International Symposium on Geoscience and Remote Sensing*, Seoul, Korea, vol. 2, pp. 1237-1240, Jul. 2005.

[4] Y. Zhou, B. Wu, D. R. Li, R. X. Li, "Edge detection on hyperspectral imagery via manifold techniques," *First workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing*, Grenoble, France, pp. 1-4, Aug. 2009.

[5] Z. Y. Zhang and H. Y. L. Zha, "Principal manifolds and nonlinear dimension reduction via local tangent space alignment," *SIAM Journal of Science Computing*, vol. 26, no. 1, pp. 313-338, Dec. 2004.

[6] L. Ma, M. M. Crawford, and J. W. Tian, "Generalized supervised local tangent space alignment for hyperspectral image classification," *Electronics Letters*. (In review)

[7] Y. Bengio, J. F. Paiement, and P. Vincent, "Out-of-sample extensions for LLE, Isomap, MDS, eigenmaps, and spectral clustering," *Advances in Neural Information Processing Systems 16*, Cambridge, MIT Press, pp. 177-184, Jul. 2003.

[8] M. D. Ferrell and R. M. Merserseau, "On the impact of covariance contamination for adaptive detection in hyperspectral imaging," *IEEE Signal Processing Letters*, vol. 12, no. 9, pp. 649-652, Sep. 2005.

[9] H. Kwon and N. M. Nasrabadi, "Kernel RX-algorithm: a nonlinear anomaly detector for hyperspectral imagery," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 43, no. 2, pp. 388-397, Feb. 2005.

[10] J. C. Tilton, "Analysis of hierarchically related image segmentations," *IEEE Workshop on Advances in Techniques for Analysis of Remotely Sensed Data*, Greenbelt, MD, USA, pp. 60-69, Oct. 2003.

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