Kernel Low-Rank Representation for Clustering and Classification

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Abstract

In this work, we are developing new approaches for robust feature selection methods that will lead to improved automated classification of explosives, both in luggage inspection and in AIT. Many explosives of interest are based on families with similar chemical composition, and can be expected to exhibit similar patterns in observed characteristics such as X-ray attenuation spectra across frequencies. Our proposed approach uses training data to identify low dimensional nonlinear manifolds around which the data points cluster. These manifolds provide a natural, low-dimensional set of features that can be used to design robust classifiers that perform well with limited training data. The algorithms are based on nonlinear extensions of linear subspace clustering techniques. The performance of the algorithms are illustrated with experiments on different data sets, including a data set of X-ray absorption spectra, and demonstrate significant improvement in clustering and classification performance over conventional techniques.

Relevance

- Robust explosives detection and classification is a critical problem in luggage inspection, AIT
- Our results provide framework for identifying low dimensional robust features from limited training data, with important advantages:
  - Improved performance for non-separable data
  - Classification of high-dimensional data with limited training samples
- Also applicable to detection, recognition in video
  - Face recognition, anomaly detection
  - Video data is high-dimensional, requires requires small set of robust features

Previous Work

Current methods such as PCA [1] and KPCA [2] rely on orthogonal subspaces to extract low-dimensional structural information. Linear Low-Rank Representation (LRR) [3] allows for recovery of non-orthogonal subspaces, however is limited to linear structures. We have developed a method that recovers nonlinear, non-orthogonal structures, Kernel Low-Rank Representation (KLRR).

Methodology

Let *X* is the available data, with each column containing the measurements corresponding to a sample object measurement

$\phi(\cdot)$ is a nonlinear mapping from the data space into a high dimensional space

Main idea: Try to separate images of data points $\phi(X)$ into small numbers of linear subspaces

Resulting problem:

$$\min_Z \frac{1}{2}\|\phi(X)-\phi(X)Z\|_F^2+\lambda\|Z\|_*$$

X : Data

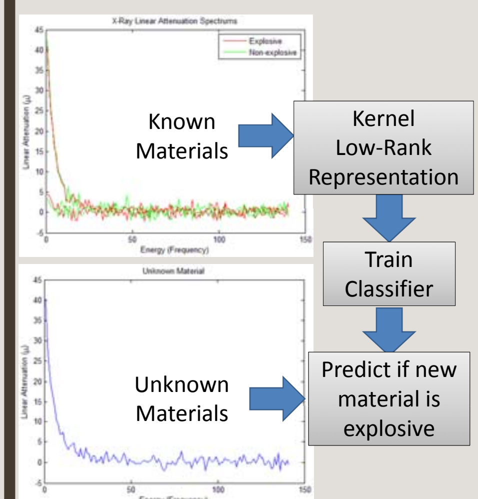
Z : Kernel LRR

$\phi(\cdot)$: Nonlinear basis function

$\|\cdot\|_*$: Nuclear Norm

Columns of *Z*, are the low dimensional representations of the data.

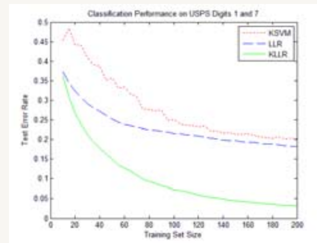
Minimization can be solved without explicitly evaluating the expanded basis, $\phi(\cdot)$, but instead by evaluating the inner products of expanded basis, represented as kernel functions. Using an Inexact Augmented Lagrange Multiplier method, we have developed an algorithm to solve this minimization.



Experimental Results

Handwriting Recognition

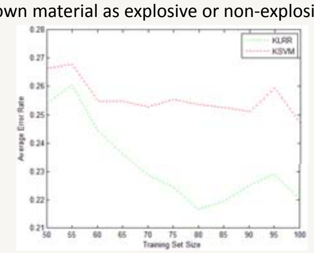
Given a set of labeled samples of the handwritten digits 1 and 7 from the USPS dataset [4], our goal was to classify unlabeled digits from noisy images.



Using a simple linear classifier on the kernelized low-rank representation, we achieved superior performance compared to linear classification on the linear low-rank representation or kernel support vector machine (SVM), whose performance was matched using 1/5 the training data, demonstrating the ability to classify with a high degree of accuracy with limited training data.

Explosive Detection

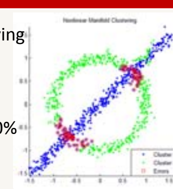
Given a set of x-ray linear-attenuation spectrums sampled at 141 energy values for a set of explosive and non-explosive materials, our goal is to classify an unknown material as explosive or non-explosive [5].



Using a linear SVM on the kernelized low-rank representation, we achieved a lower classification error rate than traditional kernel SVM methods.

Simulated Data

Clustering of simulated data lying on circle and line, traditional spatial and linear subspace clustering techniques fail, however KLRR clusters with 90% accuracy.



Opportunities for Transition to Customer

Results to date show improved classification performance on real data, especially in the case of limited training data. Of particular interest is the improved explosives detection based on absorption at multiple energies over state-of-the-art methods. We are interested in experimenting with AIT data and with multi-modal data sets, in collaboration with National Laboratory partners, and with video data sets for anomaly detection.

Future Work

Extension to video anomaly detection

Experiments with Explosives data sets

Establishment of performance bounds

Publications Acknowledging DHS Support

Joseph Wang, Venkatesh Saligrama, David Castanon, "Kernel Low-Rank Representations," *CISE-Technical Report #2011-IR-0001*.

References

[1] Jolliffe, I.T., "Principal Component Analysis." Springer-Verlag, New York, 1986.

[2] S. Mika, B. Schölkopf, A. J. Smola, K.-R. Müller, M. Scholz, and G. Rätsch, M. S. Kearns, S. A. Solla, and D. A. Cohn, "Kernel PCA and de-noising in feature spaces", in Advances in Neural Information Processing Systems, 1998.

[3] Liu, G., Lin, Z., Yan, S., Sun, J., Yu, Y., and Ma, Y. "Robust Recovery of Subspace Structures by Low-Rank Representation." ArXiv e-prints, October 2010.

[4] Frank, A. and Asuncion, A. UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science, 2010.

[5] Eger, L., Ishwar, P., Karl, W.C., Pien, H. "Classification-aware dimensionality reduction methods for explosives detection using multi-energy x-ray computed tomography," in SPIE 2011.

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