Linear Versus Nonlinear PCA for the Classification of Hyperspectral Data Based on the Extended Morphological Profiles

Paper Review

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Outline

Paper

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Linear Versus Nonlinear PCA for the Classification of Hyperspectral Data Based on the Extended Morphological Profiles

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Motivation

- Morphological Profiles (MP) extract spatial-spectral features from images.
  - To perform classification.
- It operates in single bands.
  - Usually one uses the first principal components (PCA).
- The paper compares results in hyperspectral classification:
  - Using PCA-MP.
  - Using Non-Linear PCA-MP.
- Validated on two different data sets having different spatial and spectral resolutions/coverages, over the same ground truth.
  - And using two different classification algorithms: NNs and SVM.

Outline

Morphological profiles

The idea at the base of MP is to apply geodesic closing/opening transformations of increasing size to build a certain set of opening profiles (OPs) and closing profiles (CPs). The OPs/CPs P at pixel x of the image f are defined as a p-dimensional vector

$$P_i(x) = \gamma_R^{(i)}(x) \qquad \forall\, i \in [[0, p]] \qquad (1)$$

where $\gamma_R^{(i)}$ can be the opening or closing by reconstruction with an SE of size i.

By grouping the OP, CP, and the image $f(x)$, the $(2p+1)$-dimensional vector is the MP which is defined as

$$MP(x) = [CP_p(x), \ldots, f(x), \ldots OP_p(x)]\,. \qquad (2)$$

Extended MP

It is clear from the representation of MP in (2) that applying MPs directly to the hyperspectral data with huge number of bands leads to a huge increase in the number of features. The stacking of the $q(2p+1)$ MPs obtained with different features (where q is the number of retained components) is called EMP.

Outline

Dimensionality reduction

One of the main difficulties in processing HS images is related to the very high number of spectral bands. Applying any processing technique to each band of the HS image can lead to a nonacceptable increase of the computational time of the entire process. Therefore, it is generally desirable that a reduction in the number of features is achieved without losing the relevant spectral information of the original data set. In the literature, there exist many methods for representing the information content in lower dimensionality domain, called feature extraction techniques [10].

PCA and ICA

Two of the most popular feature extraction methods for data representation are PCA, where a set of uncorrelated transformed features is generated, and Independent Component Analysis, where a computational method is used for separating a multivariate signal from additive subcomponents supposing the mutual statistical independence of the non-Gaussian source signals [11]. For these techniques, dimensionality reduction is obtained by discarding the components with the lowest information content. In addition, as most of them are linear methods, the resulting components are linearly uncorrelated, but the physical representation of the image may be lost.

NPCA

NLPCA, originally introduced by Kramer [9], is based on a multilayer perceptron commonly referred to as (AANN) or as autoencoder [12], [13]. AANNs are conventional NNs featuring feedforward connections and sigmoidal nodal transfer functions, trained by a backpropagation algorithm. The particular network architecture used employs three hidden layers, including an internal bottleneck layer of smaller dimension than either input or output. The network is trained to perform identity mapping, where the input has to be equal to the output. Since there are fewer units in the bottleneck layer compared to the output, the bottleneck nodes must encode the information obtained from the inputs for the subsequent layers to reconstruct the input. In such a way, nonlinear PCs (NLPCs) can be extracted from the bottleneck nodes after the training of AANN.

Implementing NPCA

The main task in designing AANN is the selection of the number of nodes minimizing the information losses of the training. This problem was solved by a grid-search algorithm varying recursively the number of nodes and evaluating the respective error. The topology producing the lowest error was then selected. Compared to linear reduction techniques, NLPCA has many advantages. First of all, while linear methods can detect and discard linear correlations among spectral bands, NLPCA detects both linear and nonlinear correlations. Moreover, in NLPCA, the information content is equally distributed among the components [14].

Outline

Sensors

In this section, we present the results of the proposed approach applied to two different HS images having different spatial and spectral resolutions/coverages, over the same ground truth. In both experiments, we classified the EMP built from the NLPCs extracted from a HyMap image and from a CHRIS image. HyMap is an airborne four-spectrometer sensor (VIS, NIR, SWIR1, and SWIR2), providing 128 bands across the reflective solar wavelength region of 0.45–2.5 μm with contiguous spectral coverage (except in the atmospheric water vapor bands) and bandwidths between 15 and 20 nm [Fig. 1(a)]. The CHRIS image was acquired in Mode 1 configuration, having 62 spectral bands, with a spatial resolution of 34 m at nadir and a spectral coverage of 0.45–1.03 μm [Fig. 1(b)].

Datasets

Both images were acquired over the same area during the ESA SPectra bARrax Campaign 2003 (SPARC) campaign (http://www.uv.es/leo/sparc/) carried out in Barrax, La Mancha, Spain, from 12 to 14 of July 2003. The Barrax area is mainly used for agricultural cultivations and has been investigated for many years. It is characterized by a flat morphology and large uniform land-use units, mainly composed of different agricultural types. During the campaign, an extensive ground truth was produced [Fig. 1(c)] and was used to build the ground truth in this letter. The reference classes used for the classification are as follows: Corn, Papaver, Potatoes, Alfalfa, Wheat, Barley, Garlic, Vineyards, Bare soil, Onion, and Barley stubbles, resulting in about 60.500 and 2.500 pixels for HyMap and CHRIS, respectively, equally distributed between training and test sets.

Groundtruth

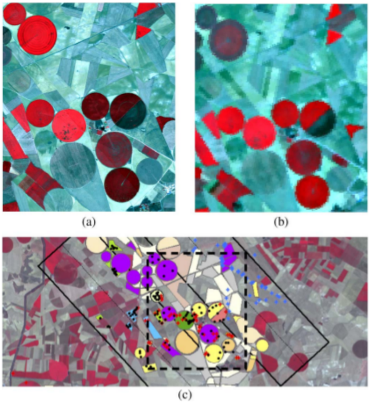

Fig. 1. False color RGB of (a) HyMap data set and (b) CHRIS. (c) The map shows the ground truth acquired during the ESA SPARC campaign.

Methodology

To evaluate the effectiveness of the method, the classification was performed by two different algorithms, i.e., NNs and support vector machines (SVMs). A comparison with the classification accuracies obtained using standard PCA and KPCA with EMP shows the enhancement introduced by NPCA. In PCA and KPCA, dimensionality reduction is performed, discarding the features that are less informative, but while in PCA most of the information content is retained in the first few features, KPCA requires more components. This means that KPCA needs a large number of components, increasing the dimensionality of the data, resulting in a huge number of features when building MPs. Moreover, in KPCA, the choices of the kernel parameter and the sample size to perform KPCA are very important, and determining these parameters is not an easy task. In particular, for both images, KPCA was performed with 1500 samples, and the kernel parameter was selected as twice the average distance between all the pixels. Tuning of these parameters was not performed because, being strongly dependent on the randomly selected sample set, it will require a further processing step, which cannot be compared with other approaches.

Results HyMAP

TABLE I
CLASSIFICATION RESULTS FOR THE HYMAP DATA SET USING SVM CLASSIFICATION ALGORITHM

Feature	Raw	*PCA*	*NLPCA*	*KPCA*
N. of features	126	5	6	15
N. of EMP		45	54	135
OA (%)	75.5792	74.1682	**79.6533**	73.1162
k	0.7252	0.7090	**0.7654**	0.6975
Corn	**99.95**	99.55	99.89	99.92
Papaver	**100**	99.52	**100**	**100**
Potatoes	96.12	99.21	**99.98**	**100**
Alfalfa	30.95	37.21	**37.39**	36.25
Wheat	99.28	95.02	99.29	**99.96**
Barley	**100**	99.66	99.74	99.57
Garlic	**100**	**100**	96.66	**100**
Vineyards	97.27	**98.98**	97.26	95.22
Bare soil	39.67	27.03	**62.91**	28.68
Barley stubbles	99.23	**99.33**	74.53	97.99
Onions	99.36	98.92	**100**	**100**

TABLE II
CLASSIFICATION RESULTS FOR THE HYMAP DATA SET USING NN CLASSIFICATION ALGORITHM

Feature	Raw	*PCA*	*NLPCA*	*KPCA*
N. of features	126	5	6	15
N. of EMP		45	54	135
OA (%)	79.6533	72.5309	**81.9068**	74.7217
k	0.7654	0.6912	**0.7930**	0.7147
Corn	**99.89**	99.55	99.73	99.48
Papaver	**100**	99.52	99.95	98.94
Potatoes	**99.98**	99.21	**99.98**	86.99
Alfalfa	37.39	37.51	**75.15**	27.06
Wheat	99.26	95.02	94.25	**99.70**
Barley	**99.74**	99.66	91.47	43.10
Garlic	96.66	**100**	99.64	99.64
Vineyards	**99.81**	98.98	99.18	93.29
Bare soil	39.67	27.03	79.14	**82.27**
Barley stubbles	99.33	68.76	75.57	**99.97**
Onions	**100**	98.92	98.66	97.96

Results HyMAP

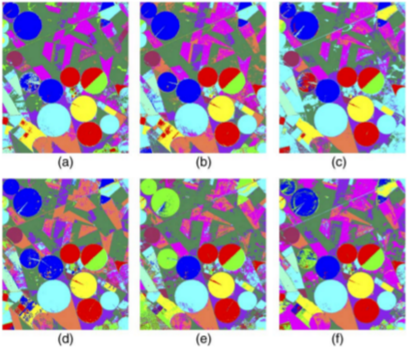

Fig. 2. Classification results obtained from the HyMap image using an SVM classification algorithm on the EMPs built from (a) PCA, (b) NLPCA, and (c) KPCA, and using an NN classification algorithm on the EMPs built from (d) PCA, (e) NLPCA, and (f) KPCA. The color map is as follows: Corn, Papaver, Potatoes, Alfalfa, Wheat, Barley, Garlic, Vineyards, Bare soil, Barley stubble, and Onions.

Results CHRIS

TABLE III
CLASSIFICATION RESULTS FOR THE CHRIS DATA SET
USING SVM CLASSIFICATION AGORITHM

Feature	Raw	*PCA*	*NLPCA*	*KPCA*
N. of features	62	4	4	15
N. of EMP		36	36	135
OA (%)	78.6342	73.8019	**85.2636**	70.0080
k	0.7513	0.6945	**0.8277**	0.6525
Corn	**100**	**100**	**100**	31.77
Papaver	**100**	**100**	**100**	**100**
Potatoes	**100**	**100**	**100**	99.17
Alfalfa	75.46	72.2	**77.87**	65.57
Wheat	**100**	**100**	**100**	**100**
Barley	**100**	**100**	40.00	**100**
Garlic	79.89	79.84	**96.12**	50.37
Vineyards	**74.89**	69.36	49.36	**100**
Bare soil	**100**	78.69	**100**	**100**
Barley stubbles	**100**	68.76	61.16	32.34
Onions	**100**	50.37	**100**	95.14

TABLE IV
CLASSIFICATION RESULTS FOR THE CHRIS DATA SET
USING NN CLASSIFICATION ALGORITHM

Feature	Raw	*PCA*	*NLPCA*	*KPCA*
N. of features	62	4	4	15
N. of EMP		36	36	135
OA (%)	89.1342	70.4872	**93.3706**	74.2259
k	0.8694	0.6647	**0.9209**	0.7094
Corn	**100**	**100**	**100**	99.89
Papaver	**100**	**100**	**100**	**100.00**
Potatoes	95.80	**100**	82.09	99.96
Alfalfa	74.74	32.62	**100**	37.39
Wheat	**100**	**100**	99.34	98.87
Barley	**100**	38.57	61.43	99.74
Garlic	**100**	**100**	92.25	96.66
Vineyards	86.19	46.38	94.86	**99.55**
Bare soil	83.72	**100**	**100**	39.67
Barley stubbles	**100**	76.86	26.45	74.53
Onions	**100**	50.37	99.26	**100**

Results CHRIS

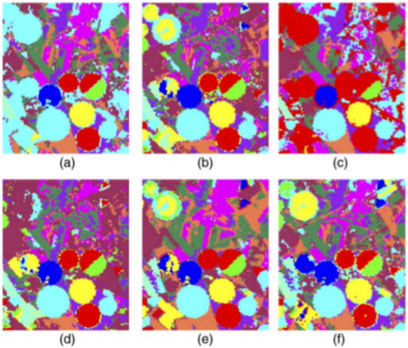

Fig. 3. Classification results obtained from the CHRIS image using an SVM classification algorithm on the EMPs built from (a) PCA, (b) NLPCA, and (c) KPCA, and using an NN classification algorithm on the EMPs built from (d) PCA, (e) NLPCA, and (f) KPCA. The color map is as follows: Corn, Papaver, Potatoes, Alfalfa, Wheat, Barley, Garlic, Vineyards, Bare soil, Barley stubble, and Onions.