MORPHOLOGICAL IMAGE DISTANCES FOR HYPERSPECTRAL DIMENSIONALITY EXPLORATION USING KERNEL-PCA AND ISOMAP

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1. INTRODUCTION: MOTIVATION AND AIM

The application of nonlinear manifold learning for hyperspectral image analysis has been widely studied in last years [1, 3]. One of the main ingredients of these data reduction techniques is the distance used to compare the spectral band images. By means of this distance the pairwise similarity matrix is built and then, the matrix is used to explore the intrinsic dimensionality of the hyperspectral image.

There are two main families of image distances which have been considered in previous works: i) the distance between the pixels using Minkowski metrics, such as the Euclidean distance or the L_1 distance; ii) the distances between the image histograms, such as the Kullback-Leibler Divergence [5] or the chi-squared distance [2]. By comparing pairwise pixels, Minkowski metrics take into account the spatial structure, however they can be very sensitive to acquisition noise of different spectral bands (L_1 is more robust to noise than L_2) or to slight spatial shifts between the different bands. Histogram distances are robust to both intensity and spatial variations but they do not consider the spatial structure. A recent work [7] has considered this lack of spatial coherence in the classical distances for nonlinear data reduction by replacing the pixelwise Euclidean distance by the Euclidean distance between neighbour patches ($n \times n$ surrounding pixels centred at each pixel).

The aim of this paper is to propose two new families of spatial image distances for spectral band comparison. Both are based on notions from mathematical morphology [9], a nonlinear image processing methodology based on the application of lattice theory to spatial structures. The first distance is based on the formulation using morphological dilations of Hausdorff distance for gray-scale images [10]. The second distance is more original and it is founded in the leveling operator [6]. Levelings are geodesic filters which modify, without blurring the contours, one of the images according to the other image. The application of these morphological distances for hyperspectral dimensionality exploration is illustrated with two powerful nonlinear data analysis techniques: Kernel-PCA and ISOMAP. Using standard image examples, their performance is studied in comparison with other image distances such as Euclidean distance of patches and KL-divergence.

2. REMAINDER ON KERNEL-PCA AND ISOMAP

Kernel PCA is a nonlinear generalization of Principal Component Analysis. By choosing nonlinear kernels adapted to data nature, the dimensionally reduction is usually stronger than using linear PCA. In practice, classical and effective kernels are based on a function of a distance between the points, such as the radial basis function kernel. In our case, the distance corresponds to the distance between the two spectral bands.

Isometric feature mapping (Isomap) is a method for estimating the intrinsic geometry of a data manifold based on a rough estimate of each data point neighbours on the manifold. More precisely, it is a low-dimensional embedding approach based on geodesic distances on a weighted neighbourhood graph and multidimensional scaling (MDS). Again a distance between the spectral bands is needed to build the neighbourhood graph.

3. MULTI-SCALE HAUSDORFF DISTANCES

The well known Hausdorff distance is a natural metric for comparing sets (i.e., binary images). Its extension to scalar functions (i.e., gray level images) allows comparing also the image structures of spectral bands. The value of distance represents the “size” of the dilation in such a way that one image covers totally the other. In addition, before computing the Hausdorff distance, the images can be simplified by removing the structures of a certain scale or size and then compute the Hausdorff distance. In such a case, a value of Hausdorff distance is obtained for each scale and the final global distance can be obtained as the sum or the max of the different scale distance values. Several morphological filters are considered to define the multi-scale decomposition pyramid.

4. LEVELING-BASED MORPHOLOGICAL DISTANCES

A leveling filter has two input images: the reference image and the marker image (which is generally a rough simplification of the reference image), and it simplifies textures and eliminates small details of the reference image according to the marked structures, but preserving the contours of remaining objects. In fact, the leveling is obtained by iteration of geodesic dilations and erosions until idempotence. Consequently, besides the final levelled image, a series of images (successive modifications of marker to approach the reference) is obtained.

Given two spectral images, two associated leveling images (and their corresponding intermediate image series) are obtained, depending on which is used as reference and which as marker. Instead of computing the distance between the original spectral images, the basic idea of the new distance is to calculate a spatial distance (using for instance the Euclidean distance) between both leveling images. There are other possible variants, as computing the spatial distance of residue images or, as for the Hausdorff framework, the distance vector between the different steps of the leveling.

In comparison with standard Minkowski metrics, the levelling-based distances take into account the "scale" of the structures which are different and it is more robust against effects owing to noise or spatial shifts.

5. EXPERIMENTS AND RESULTS

Two dataset are used in the examples. The first dataset is the hyperspectral image of the Indian Pines, obtained by the AVIRIS sensor. The other dataset is an airbone image from the ROSIS-3 optical sensor of the University of Pavia. The performance of the morphological distances is studied in comparison with other image distances such as Euclidean distance of patches and KL-divergence.

6. REFERENCES

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