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ARTÍCULO DE INVESTIGACIÓN

Exploration of Fourier shape descriptor for classification of hyperspectral imagery

Exploración del descriptor de forma de Fourier para la clasificación de imágenes hiperespectrales

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Abstract

Spectral signatures collected by hyperspectral remote sensors provide useful information about the objects and materials in the sensor field of view. Dimensional reduction techniques are used to transform the spectral signature into a new lower dimensional space. However, most of the dimensional reduction approaches do not take into account the shape of hyperspectral signatures. In this paper, we present a study about Fourier shape descriptors to obtain lower-dimension representation of spectral signatures for hyperspectral image classification. We compare principal component analysis –PCA, a widely used dimensional reduction technique, with the representation obtained from Fourier shape descriptors. A super vector machine classifier is used to compare PCA and Fourier shape descriptors in the classification of Indian Pines, which is an AVIRIS hyperspectral image collected over an agriculture field. Fourier shape descriptors improve the classification accuracy, in the same time that fewer descriptors are used.

Palabras clave: hyperspectral imagery, classification, dimensional reduction, Fourier shape descriptor.

Resumen

Las firmas espectrales capturadas con sensores hiperespectrales remotos proporcionan información útil sobre los objetos y los materiales en el campo de visión del sensor. Técnicas de reducción de dimensiones son usadas para transformar las firmas espectrales en espacio de dimensión más baja. Sin embargo, la mayoría de estos enfoques de reducción de dimensiones no tienen en cuenta la forma de las firmas espectrales. En este artículo, se presenta un estudio sobre los descriptores de forma de Fourier para obtener una representación de baja dimensión de firmas espectrales para la clasificación de imágenes hiperespectrales. Comparamos el análisis de componentes principales –PCA, una técnica de reducción de dimensiones ampliamente usada, con la representación obtenida desde los descriptores de forma de Fourier. Un clasificador de máquinas de soporte vectorial es usado para comparar PCA y los descriptores de forma de Fourier en la clasificación de Indian Pines, la cual es una imagen hiperespectral de AVIRIS capturada sobre un campo agrícola. Los descriptores de forma de Fourier mejoran la precisión de

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clasificación al mismo tiempo que pocos descriptores son empleados.

Keywords: imágenes hiperespectrales, clasificación, reducción de dimensiones, descriptor de forma de Fourier.

INTRODUCTION

Remote sensors allow the characterization of the atmosphere, the terrestrial surface and the oceans for Earth observation. Examples of remote sensing systems are the multispectral and hyperspectral sensors that collect both spatial and spectral information. Multispectral sensors have a relatively small number of non-contiguous bands (i.e. less than 25 bands). Instead, hyperspectral imagers have the capability to sample continuously the electromagnetic spectrum at very high spectral resolution. Spatial and spectral information from these sensors are like a cube, where each pixel is a spectral signature that characterizes the materials on the surface. The full spectral information allows the remote identification of objects and materials in the sensor field of view (Shaw & Manolakis, 2002; Plaza et al., 2009).

Two of the most used processing techniques for multispectral and hyperspectral imagery are classification and unmixing (Shaw & Manolakis, 2002). Image classification identifies information classes within a dataset and assigns labels to each pixel. Classification is based on either: rules learned from training samples (supervised learning) or from iterative processes (unsupervised learning). We can identify the information classes into a hyperspectral image using common classifiers like super vector machine –SVM (Camps-Valls & Bruzzone, 2005). However, the high number of collected spectral bands difficult the classification of hyperspectral data (Shaw & Manolakis, 2002; Plaza et al., 2009).

A way to deal with the high dimensionality of hyperspectral data is using dimensional reduction techniques (Harsanyi & Chang, 1994; Wang & Chang, 2006; Rodarmel & Shan, 2002). The most common reduction dimensional technique is principal component analysis -PCA (Shaw & Manolakis, 2002). PCA transforms a dataset into a new representation space such that the components are uncorrelated and usually ordered by decreasing variances. The main advantage of PCA is that preserves the image variances in few dimensions (Schowengerdt, 1997). However, PCA, like most of dimensional reduction techniques, does not take into account the shape of spectral signatures.

In this paper, we explore the use of Fourier shape descriptors to generate a lower representation space for hyperspectral imagery. Fourier shape descriptors are used to characterize two-dimensional shapes for object recognition in digital image processing (Gonzalez & Woods, 2008; Persoon & Fu, 1977). We extend its use to hyperspectral signatures assuming that a spectral signature is a two-dimensional boundary. Next section described the Fourier shape descriptors for hyperspectral signatures. Then, a comparison between PCA and Fourier descriptors is performed using a real hyperspectral image.

FOURIER SHAPE DESCRIPTORS

Let a pixel $s=I_j$ from a hyperspectral image I with n pixels and p spectral bands. The spectral information of s can be seen as a two-dimensional p-point shape in the xy-plane, as show in Fig. 1. Coordinate pairs, (x_κ, y_κ) for $k=0,2,\ldots,p-1$, are obtained from the band number and their corresponding reflectance values. Each coordinate pairs can be seen as a complex number: $s_\kappa=x_\kappa+iy_\kappa$, which real part x_κ equal to the band number from the κth spectral band and imaginary part y_κ equal to the reflectance in the κth spectral band.

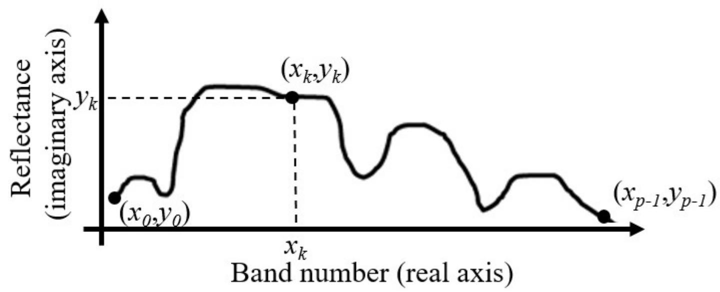

Figura 1. Coordinate pair representation of a pixel *s* with *p* spectral bands

Given *p* consecutive points s_κ, $0 \leq \kappa \leq p\text{-}1$, the *p*-point discrete Fourier transform –DFT S_l, $0\leq l \leq p\text{-}1$, is defined by:

$$S_l = \sum_{k=0}^{p-1} s_k e^{-i\frac{2\pi}{p}kl} \qquad (1)$$

The coefficient magnitude $|S_l|$ are the Fourier descriptor for the shape *s*.

Supervised Classification using Fourier Shape Descriptors

The classification of hyperspectral imagery based on Fourier shape descriptors is performed according Fig. 2. The hyperspectral image is assumed already with atmospheric correction. First, the complex sequence $s_\kappa=x_\kappa+iy_\kappa$ is built, and then the Fourier shape descriptors using eq. (1) are obtained. In this step, we need to set *m*, the number of Fourier descriptors. In this paper, we compare the overall classification accuracy using several number of shape descriptors. A subset from obtained Fourier descriptors are used as training samples for a supervised classifier like SVM. Finally, the full set of Fourier descriptors are classified using the trained machine. Next section describes the dataset, implementation and results for this classification framework.

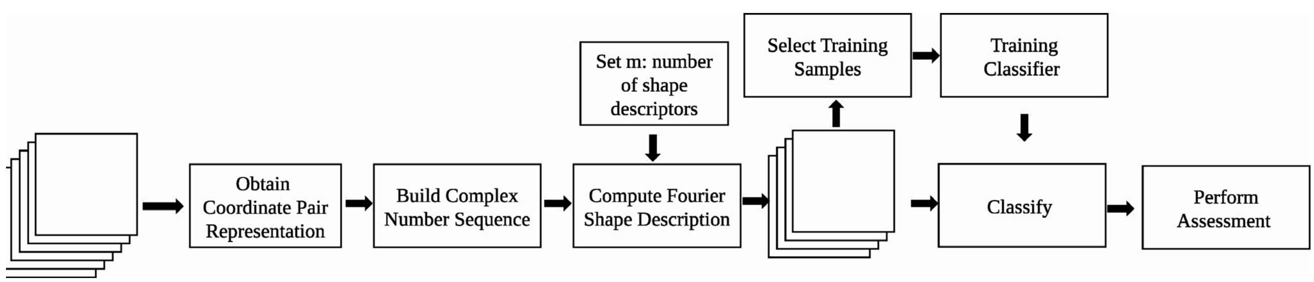

Figura 2. Supervised classification of hyperspectral imagery using Fourier shape descriptors

EXPERIMENTS

Dataset

The image used to evaluate the Fourier shape descriptors was Indian Pines. This is a hyperspectral image collected over a rural region in West Lafayette, Indiana in 1992 using AVIRIS sensor. This image is widely used to test classification algorithms for hyperspectral image processing. The image has 224 spectral bands and 145x145 pixels. The image and a ground truth classification maps are available online (https://engineering.purdue.edu/~biehl/MultiSpec/hyperspectral.html). The classification map includes 16 classes with different types of corn and soybean. Only 200 spectral bands are used in the process. Spectral bands corresponding to the water absorption were removed (104-108, 150-163 and 220). Fig. 3 presents the RGB composition of Indian Pines and Fig. 4a shows the classification map.

Figura 3. Composition RGB for Indian Pines. Red plane: band 30 (654.5 nm), Green plane: band 20 (557.7 nm) and Blue plane: band 9 (451.3 nm).

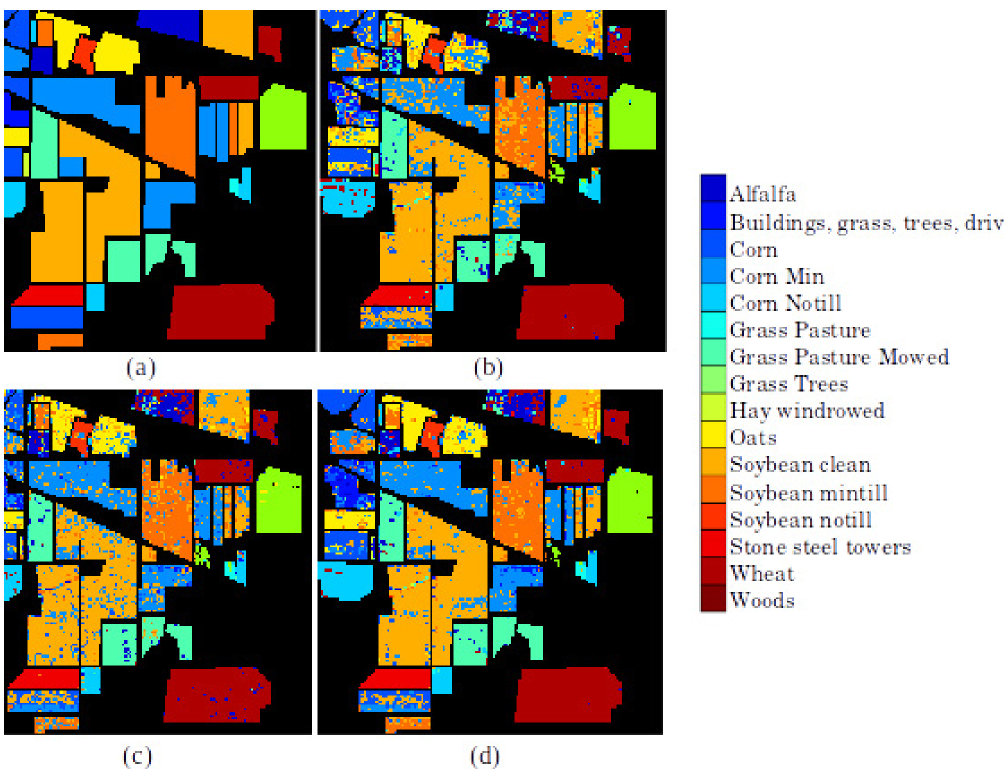

Figura 4. Indian Pines classification maps: (a) ground truth, (b) original image, (c) 15 principal components, and (d) 15 Fourier descriptors.

Table 1. Overall accuracies for Indian Pines image using SVM.

Class	Original Image (%)	15 PC (%)	15 FD (%)
Alfalfa	37.04	27.78	61.11
Buildings	44.21	59.21	57.89
Corn	41.03	47.01	59.40
Corn Min	56.12	60.07	69.78
Corn Notill	66.88	74.27	76.71
Grass Pasture	86.32	86.92	94.97
Grass Pasture Mowed	73.08	73.08	84.62
Grass Trees	89.02	90.63	92.90
Hay Win-drowed	98.98	97.75	98.36
Oats	20.00	40.00	45.00
Soybean Clean	56.68	71.34	79.64
Soybean Mintill	85.70	80.15	86.79
Soybean Notill	66.22	71.80	76.86
Stone	83.16	83.16	91.58
Wheat	96.23	99.06	99.53
Woods	95.29	95.29	98.69

Table 2. Per class accuracies for Indian Pines image using SVM.

	Original Image	76.52%
nc	**PCA (%)**	**Fourier (%)**
5	77.44	74.34
10	**78.50**	82.84
15	78.75	**83.95**
20	77.43	83.31
25	74.24	81.08
30	70.52	78.01
35	67.02	76.83
40	64.19	75.16

Implementation

In this work, a SVM classifier with a second order polynomial kernel was used to compare the Fourier descriptors with PCA. We used both fitcecoc and predict from the Statistic and Machine Learning Toolbox of MATLAB to train and test SVM. Fourier shape descriptors were computed used fft function of MATLAB. We selected randomly 10% of the samples per class like training samples. The same training samples were used to train the classifier for the original image, PCA and Fourier descriptors. The classification results are assessed using all labeled samples available into the ground truth map.

Results

Table 1 presents the overall accuracies from the original image, PCA and Fourier descriptor classifications respectively. The number of principal components and Fourier descriptors were varied between 5 and 40. Table 2 presents the accuracy classification per class obtained from the original image without any dimensional reduction technique, 15 principal components and 15 Fourier descriptors. The classification maps obtained from the original image, the 15 principal components and the 15 Fourier descriptors are compared in the Fig. 4. Background or unlabeled pixels were ignored and set to black into the classification maps (Fig. 4).

ANALYSIS OF RESULTS

In the Table 1, it can note that SVM obtained an overall accuracy equal to 76.5% using the original image without any dimensional reduction. Instead, using only 15 principal components, SVM obtained an overall accuracy equal to 78.7%. However, the best classification results were obtained using 15 Fourier descriptors with a 83.4% of overall accuracy. In general, the accuracies obtained from the Fourier descriptors were better than the obtained from PCA.

Note that is necessary to determine a suitable number of Fourier descriptors. Table 1 shows that the accuracy depends on the number of Fourier descriptors. For instance, the overall accuracies are lower using either 5 or 40 Fourier descriptors than the accuracy obtained from the original image without any dimensional reduction technique. Best classification results were obtained using between 10 and 35 Fourier descriptors.

On other hand, better per class accuracies were obtained using few Fourier descriptors instead the original dataset and principal component analysis (see Table 2). Note that 15 Fourier descriptors improved significantly the classification accuracies for alfalfa, corn, corn min, corn notill, grass pasture, grass pasture mowed, oats, soybean clean, soybean notill, and stone classes. In addition, Fourier descriptors preserve high accuracy results for grass pasture, grass trees, hay windrowed, wheat and woods classes. Only the building and hay windrowed classes are better classified from principal components and original image respectively.

Fourier shape descriptors have a high potential to improve hyperspectral image classification according the obtained results. Fig. 4d evidences that Fourier shape descriptors outperform PCA (Fig. 4c) to obtain a lower-dimension representation that improves the classification of hyperspectral imagery.

CONCLUSIONS

Fourier shape descriptors describe two-dimensional digital boundaries for objet recognition in digital image processing. In this paper, we extend the use of Fourier shape descriptors to find a lower-dimensional representation for hyperspectral data that improves classification results. A comparative study between Fourier shape descriptors and principal component analysis was performed. We show that Fourier shape descriptors outperform principal component analysis. Fourier descriptors allowed to obtain higher overall and per class classification accuracies for Indian Pines.

In a future work, we will explore the use of Fourier shape descriptors with other real hyperspectral imagery, as well as, it is necessary to study the automatic selection of the number of Fourier shape descriptor. On other hand, other two-dimensional shape descriptors can be explored to improve the classification of hyperspectral imagery.

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