Kernel Based Spectral Image Segmentation

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Abstract

In this work, we propose a new algorithm for spectral image segmentation based on the use of a kernel matrix. An efficient multiscale method is presented for accelerating spectral image segmentation. The multiscale strategy uses the lattice geometry of images to construct an image pyramid whose hierarchy provides a framework for rapidly estimating eigenvectors of normalized kernel matrices. To prevent the boundaries from deteriorating, the image size on the top level of the pyramid is generally required to be around 75×75, where the eigenvectors of normalized kernel matrices would be approximately solved by the Nyström method. Within this hierarchical structure, the coarse solution is increasingly propagated to finer levels and is refined using subspace iteration. Experimental results have shown that the proposed method can perform significantly well in spectral image segmentation as well as speed up the approximation of the eigenvectors of normalized kernel matrices.

Introduction

Spectral image segmentation has drawn a lot attention [5, 8, 9, 10, 12, 13] in recent years due to its potential applications in forest assessment, mineral exploration, medical imaging, and so on. The main advantage of spectral images comprising more than 20 spectral bands is the large amount of color information involved, which dramatically improves the ability to detect individual materials or separate areas with visually different colors.

Paclik et al. combined standard pattern recognition algorithms and proposed a new segmentation algorithm in [12]. Crespo et al. presented in [5] a segmentation system that consists of a set of neural networks based on Gaussian synapse. In [13], Pal and Mitra addressed the problem of segmentation by integrating rough-set theory, the EM algorithm and minimal spanning tree clustering. Mercier et al. [9] have developed a method for the segmentation of a spectral data cube based on hidden Markov chain. Mohammad-Djafari et al. [10] proposed a Bayesian estimation approach with an appropriate hierachical model with hidden markovian variables. In [8], Kwon and Nasrabadi realized a kernel matched subspace detector (KMSD) to partition targets from a spectral image. However, almost all of these methods were developed for special purposes or had limitations in their practical applications. And, most of these methods viewed each pixel in a spectral image as a multdimensional vector and did not consider characteristics of spectra such as geometric features. To address these problems, therefore, a kernel based approach to spectral image segmentation is proposed in this paper.

In spectral spaces, each color is represented by a spectral curve; thus, pixel values in spectral images generated by spectral imaging sensors correspond to a vector whose entries describe the energy value in some wave band. Although spectral curves of an image are distinct, homogeneous regions are, in general, characterized by similar spectra. In other words, the wealth of spectral information available in color spectra provides critical cues for distinguishing colors and regions. To make full use of the abundant color information contained in spectral images, we take into consideration the geometric features as well as the magnitude of spectra in calculating the similarity between pixels.

In this paper we present a spectral kernel clustering method for multiple clusters and apply it to spectral image segmentation[1]. Spectral methods for image segmentation are based on eigendecomposition of an affinity matrix. Weiss stated in [16] that the affinity matrix contains information about segmentation from visual inspection, and pointed out that, by using the top eigenvectors of such a matrix simultaneously, one could extract a representation that leads trivially to a discrete segmentation. In [11], Ng. et al. proposed a spectral clustering approach and gave conditions under which eigenvectors could be used to compute a reasonable cluster. Yu and Shi have provided in [18] a discretization method to find group indicators from obtained eigenvectors. Cristianimi et al. [6] generalized spectral methods from affinity matrices to kernel matrices and proposed two cost functions to measure the quality of the bipartitioning of a data set.

The key to spectral kernel clustering is to extract a feature space spanned by several leading eigenvectors of a normalized kernel matrix. Due to the huge amount of data in spectral images, constructing and solving a kernel matrix become difficult, even impossible, on common computers. To save computational and storage costs, we introduce the multiscale strategy combined with the Nyström method [7]. This strategy first downsamples spectral images and builds a hierarchical structure, such as a pyramid. Eigenvectors are computed on the top scale of the pyramid using the Nyström method and then are propagated to finer scales, based on the similarity between neighboring pixels.

Experiments showed that the combination of the multiscale and Nyström methods can prevent boundaries deteriorating between homogeneous regions during downsampling. Thus, our approach has been shown to be effective in providing good segmentation while speeding up the estimation of eigenvectors of large matrices. In addition, the proposed method for spectral image segmentation is robust to illumination changes and sensitive to changes in color arising from hue or chroma.

[1] Please note that the word 'spectral' appears twice in this sentence and has completely different meanings in each case: the former is a mathematical concept and represents the eigenvalues of a matrix; the latter is a physical concept and is used to describe the distribution of energy emitted by a radiant source.

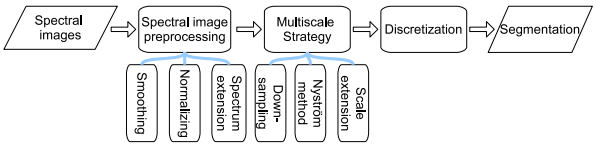

Figure 1. *A three-stage flowchart of spectral image segmentation: spectral image preprocessing, multiscale strategy and discretization.*

Spectral Image Preprocessing

As shown in Fig. 1, the proposed approach to spectral image segmentation can be divided into three stages: preprocessing, multiscale strategy and discretization. Given a spectral image, we first implement image preprocessing through smoothing, normalizing and spectrum extension. In spectrum extension, we concatenate magnitude, slope and curvature of spectra and form a fused space in which the similarity between color spectra is computed. Then our multiscale strategy is used to fast solve eigenvectors of the normalized kernel matrix. The image is downsampled in the spatial domain to produce an image pyramid. On the top scale of the pyramid, the eigenvectors are approximated with the Nyström method and are subsequently propagated into the other scales of the pyramid. The procedure of propagating from coarse to fine scales is called *scale extension*. Finally, the segmentation result could be obtained by discretizing the eigenvectors on the original scale. The discretization method we adopt was proposed by Yu and Shi in [18], which uses an alternating optimization procedure.

Spectral Images

An s-band spectral image is a two-dimensional grid ($\mu \times \nu$) of pixels, with an s-dimensional vector for each pixel. μ and ν denote the height and width of an image. Therefore, a spectral image can be viewed as a set of spectra Θ composed of l (l=$\mu\nu$) data with s spectral bands. One of the important characteristics of spectral images is that they contain a large number of spectral channels in the optical wavelength range. The number of channels can vary from tens to hundreds. Compared to color images in the RGB space, spectral images have a clear advantage in terms of describing color objects.

Smoothing and Normalizing

To remove noise arising during spectral image acquisition, it is necessary to do smoothing before segmentation. In our work, *smoothing* has two aspects: smoothing of spectral curves via a cubic spline curve and reducing spots or small regions while preserving edges in each component image via median filtering.

It is known that spectral curves incorporate three types of color information: hue, light and chroma. To cluster different colors in a correct way, normalization is necessary. Normalization could reduce the effect of illumination that does not provide useful information for color clustering. The first step of normalizing spectra is to do centering by subtracting the mean of the spectral data from each spectral value. Subsequently, the norm of the spectral data is made equal to 1 in the Euclidean sense by dividing each spectral value by the square root of the sum of squares of the spectral data.

For instance, given a set of spectra Θ composed of l data with s spectral channels,

$$\Theta = \begin{pmatrix} \theta_1 \\ \vdots \\ \theta_i \\ \vdots \\ \theta_l \end{pmatrix} = \begin{pmatrix} \theta_1^1 & \cdots & \theta_1^j & \cdots & \theta_1^s \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \theta_i^1 & \cdots & \theta_i^j & \cdots & \theta_i^s \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \theta_l^1 & \cdots & \theta_l^j & \cdots & \theta_l^s \end{pmatrix},$$

the normalization is done by first

$$\theta_i^j = \theta_i^j - \frac{1}{s}\sum_{k=1}^{s}\theta_i^k, \tag{1}$$

then

$$\theta_i^j = \frac{\theta_i^j}{\sqrt{\Sigma_{k=1}^{s}(\theta_i^k)^2}}. \tag{2}$$

Spectrum Extension

In this work, we described the geometric shape of color spectra by the slope Φ and curvature Ψ of spectral curves that can be computed with finite difference methods. Since curve smoothing is done at the preprocessing stage, we can efficiently use finite difference methods to approximate the slope and curvature of spectral curves.

For the analysis of spectral images, we need to incorporate not only the magnitude but also the geometric features of spectra into the similarity measure because the geometric shape of spectral curves contains significant cues about clustering as well. The natural way of combining magnitude, slope and curvature of spectra is to directly concatenate them after weighting. As a result, we get a fused space Δ=$\{\delta_i\}_{i=1}^{l}$. The combination procedure is called *spectrum extension*. We use weight coefficients, α, β and γ, such that $0\leq\alpha$, β, $\gamma\leq 1$ and α+β+γ=1, as impact factors of these three attributes to adjust their contribution to the similarity measure. Due to the fact that α+β+γ=1, we actually only need to preset two parameters. In this work, α and β were used as free parameters.

Spectral Kernel Clustering

The spectral kernel clustering method draws inspiration from [6]. Since a $l\times l$ kernel matrix K can represent the similarity between l elements (data points or pixels), we can use K to predict whether two elements are in the same cluster. Spectral kernel clustering can be treated as a problem of minimizing the inter-cluster similarity by virtue of K

Let $Y\in\mathbb{R}^{l\times r}$ be the indicator matrix, each column of which, i.e., $y_t \in \{0,1\}^l$, has nonzero components exactly at points that belong to the t-th cluster. Finding an indicator matrix Y leads to an eigendecompositon problem. Let Z=$D^{1/2}Y$ and impose a constraint on Z: Z^TZ=I_r, where I_r denotes the $r\times r$ identity matrix. Let

$$P = D^{-1/2}KD^{-1/2}, \tag{3}$$

which is essentially the normalization of kernel matrix K. Relaxing Z into the continuous domain turns the discrete problem into a tractable continuous optimization problem whose solutions involve the first r largest eigenvectors V of P [3].

To find the indicator matrix, we need to discretize the continuous solution of Y=$D^{-1/2}Z$, where the rows of Y are those of Z scaled by inverse square root of D since $D^{-1/2}$ is diagonal. Here we adopted the discretization method Yu and Shi proposed in [18].

The Multiscale Strategy for Spectral Image Segmentation

Spectral clustering methods are extremely attractive in that they are based on eigendecomposition algorithms whose stability is well understood. Nevertheless, eigendecomposition not only is time-consuming but also requires a huge amount of memory space in the context of segmentation. Some works to address such problems have recently appeared and can be divided into two categories: one is based on the Nyström method in [2, 7, 17]; the other builds on the hierarchical structure of the image pyramid [4, 14, 15]. Both of them have individual drawbacks: 1) the Nyström method is still restricted to the size of image(e.g., when the image resolution is 300×300, it is almost impossible to compute eigenvectors using the method presented in [7]); 2) in the coarse level of the multiscale strategy, the contours or shapes of homogeneous regions tend to become blurry.

To overcome the drawbacks, we combine these two classes of methods in spectral image segmentation and adopt the Nystöm method only on the top scale of the pyramid. We assume that the contours in an image can be faithfully preserved when this image is downsampled till the spatial resolution is around 75×75. In this case, the number of scales h is determined in terms of the expression below,

$$h = 1 + \max(\lceil \log_2 \frac{\max(\mu, \nu)}{150} \rceil, 0), \tag{4}$$

where the symbol $\lceil \cdot \rceil$ denotes rounding to the nearest integer towards positive infinity.

In our multiscale strategy, we first downsample the input spectral image in the spatial domain and construct an image pyramid. The downsampling procedure is quite simple. One-time downsampling is composed of two steps. We first take a pixel every two pixels along the horizontal direction on the original image; then do the same along the vertical direction on the image obtained after horizontal sampling. After sampling in both horizontal and vertical directions, we can get an image on a coarser scale. If the downsampling procedure is repeated h-1 times, h-1 different scales will be produced. Linking all these scales and the original scale together will generate a h-level image pyramid.

The Nyström Method

On the top of the pyramid, the Nyström method proposed in [7] is used to approximately solve eigenvectors V of the normalized kernel matrix P (3). Let matrix P be partitioned by randomly choosing n columns and rows into four blocks

$$P = \begin{bmatrix} A & B \\ B^T & C \end{bmatrix},$$

where A is a $n \times n$ symmetric matrix, B is of size $n \times (l\text{-}n)$ and C is a $(l\text{-}n) \times (l\text{-}n)$ symmetric matrix. According to the Nyström method, C can be approximated with $B^T A^{-1} B$; therefore, it is possible to approximately compute P as

$$\hat{P} = \begin{bmatrix} A & B \\ B^T & B^T A^{-1} B \end{bmatrix}.$$

The quality of approximation of P can be estimated via the norm of $\|C - B^T A^{-1} B\|$. As discussed in [7], selecting about 1 percent of all data to form matrix A, i.e., $n \approx 0.01l$, is generally enough for reconstructing the original normalized kernel matrix P well.

Let $G{=}A + A^{-1/2} B B^T A^{-1/2}$ and diagonalize it as $G = U_G \Lambda_G U_G^T$. Defining matrix V as

$$V = \begin{bmatrix} A \\ B^T \end{bmatrix} A^{-1/2} U_G \Lambda_G^{-1/2}, \tag{5}$$

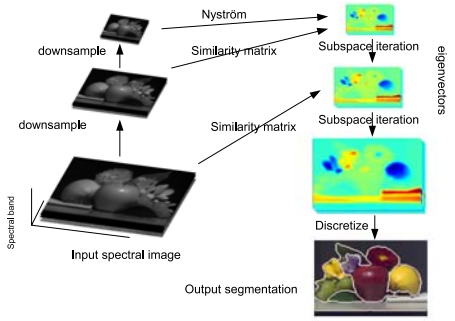

Figure 2. *Multiscale segmentation of spectral images. Left: downsampling input spectral images. Right: the upper three images represent the approximated eigenvectors and the bottom one is the segmentation result.*

we can conclude that $\hat{P}$ is diagonalized by V and Λ_G, i.e., $\hat{P} = V \Lambda_G V^T$ and $V^T V = I$.

In the procedure described above, computing G and V presents a challenge. It is clear that the computation complexity in these two steps is $\mathbf{O}(ln^2 + nl^2)$. It remains fairly prohibitive if the image size is more than 300×300.

The Segmentation Algorithm

Given a spectral image of size $\mu \times \nu \times s$, the number of segments r and weight coefficients α and β,

1. Implement spectral image preprocessing by smoothing, normalizing (Eqs. 1 and 2) extending spectra and generating the fused space Δ by using α and β.
2. Compute the number of scales h using Eq. 4 and downsample the image in the spatial domain to form an image pyramid with h scales.
3. Construct and normalize kernel matrix K_i using Eq. 3 in Δ. Here we use K_i (i=1, $\cdots$, h) to denote a similarity matrix on the i-th scale and likewise for D_i, P_i and V_i.
4. Compute the first r largest eigenvectors V_i of matrix P_i using the Nystöm method (Eq. 5) on the top of the pyramid (i.e., i=h).
5. Extend current eigenvectors V_i to V_{i-1} on the i-1-th scale according to the similarity between neighboring pixels and refine V_{i-1} with P_{i-1} using subspace iteration, until eigenvectors V_1 on the original scale are obtained.
6. Discretize $D^{-1/2} V_1$, by using the discretization method proposed in [18], to get the segmentation indicator matrix Y.

The schematic illustration of the multiscale strategy for spectral image segmentation is shown in Fig. 2. It is worth noting that matrices K and P, except on the top level where P is approximated by $\hat{P}$, are quite sparse since only the similarity between pixels in the 8-neighborhood needs to be worked out.

Experiments

This section presents the results of experiments conducted to evaluate and analyze the performance of the proposed method for spectral image segmentation. Here we mainly investigate the ability of the proposed method to produce reliable segmentations on spectral images with a variety of properties. All the spectral images we use are available in [1]. To highlight boundaries between segments, we impose boundaries on the color image reproduced from the input spectral image (as in Fig. 3).

The tested spectral images are introduced in Table I. They vary greatly in terms of content, image size and spectral resolu-

TABLE I
Tested spectral images

Image	Size	Kernel Function	Parameters			
			h	r	α	β
pentest	141×153×81	*ANOVA*	2	5	0.50	0.50
braltest	141×131×81	*ANOVA*	1	5	0.60	0.30
younggirl	147×87×61	*ANOVA*	1	3	0.50	0.50
scene	256×256×31	*Gaussian*	2	3	1.00	0.00
jussi	806×650×31	*polynomial*	4	3	0.35	0.35
toy1	363×330×31	*ANOVA*	3	3	0.34	0.33
toy2	660×330×31	*ANOVA*	4	3	0.60	0.30
toy3	600×564×31	*ANOVA*	3	4	1.00	0.00
toy4	344×576×31	*ANOVA*	3	4	0.60	0.40

tion: some of them have clear features of highlight (e.g., pentest, braltest and toy1) or shadow (e.g., braltest, scene and toy2) and the others either have abundant color information (e.g., toy2, toy3 and toy4), or depict natural scenery (e.g., scene) and human body (e.g., younggirl and jussi). We used the ANOVA kernel in all cases except for the Gaussian kernel in the "scene" image and the polynomial kernel in the "jussi" image. Parameters were set in an optimal way as shown in Table I. r, α and β were input beforehand and h was estimated automatically during segmentation. The segmentation results are shown in Fig. 3. Despite the variation of these images, the proposed method can work significantly well under all circumstances. This further strengthens our arguments: 1) the proposed approach to spectral image segmentation is quite stable and is robust to illumination changes, from highlight to shadow; 2) it is sensitive even to slight changes in color arising from hue or chroma.

Because simple eigendecomposition is done only on the top level, the proposed algorithm is efficient. Moreover, it can use massive parallel processing, especially at the finer (i.e., the most expensive) scales. Our current implementation takes less than 1 min to complete all the computations for an 800×600×31 spectral image using Matlab on a Pentium 4, 3.0-GHz processor. Further optimization is still possible on a parallel computer.

Conclusions

In this work, we put forth an approach to spectral image segmentation. We propose combining the multiscale and Nyström methods in spectral image segmentation that can accelerate the computation of eigenvectors of a normalized kernel matrix. We also propose slope and curvature of color spectra to incorporate geometric features of spectra into similarity measures, which can make full use of abundant color information contained in spectral images. The experimental results showed that the proposed approach to spectral image segmentation performs very well in distinguishing different colors in terms of hue and chroma.

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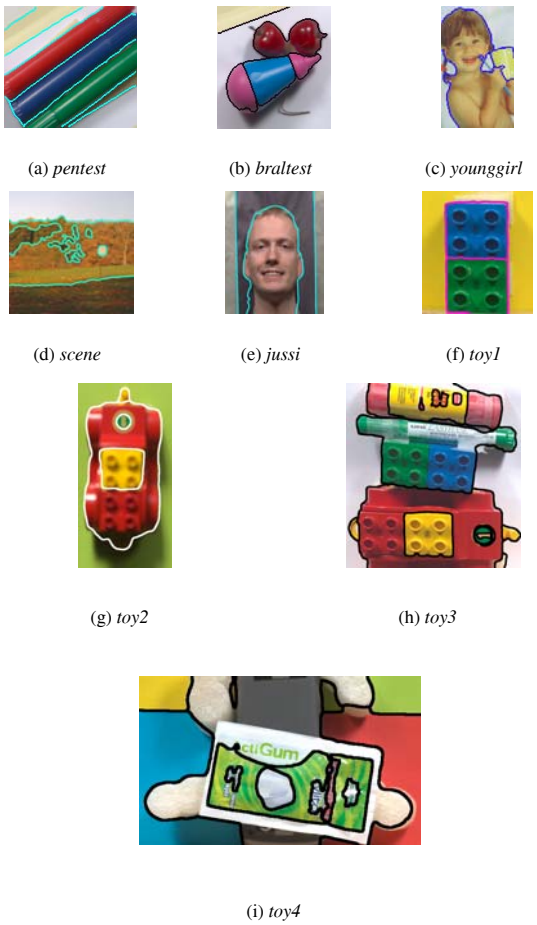

(a) *pentest* (b) *braltest* (c) *younggirl*

(d) *scene* (e) *jussi* (f) *toy1*

(g) *toy2* (h) *toy3*

(i) *toy4*

Figure 3. *The segmentation of spectral images with a variety of properties. For the ease of visualization, we put the boundaries between different segments on the corresponding RGB images.*

research interests include image analysis, manifold learning and clustering.

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