A Method for Edge Detection in Hyperspectral Images Based on Gradient Clustering

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Abstract

Edge detection in hyperspectral images is an intrinsic difficult problem as the gray value intensity images related to single spectral bands may show different edges. The few existing approaches are either based on a straight forward combining of these individual edge images, or on finding the outliers in a region segmentation. We propose as an alternative a clustering of all image pixels in a feature space constructed by the spatial gradients in the spectral bands. An initial comparative study of various hyperspectral datasets shows the differences and properties of these approaches and makes clear that the proposal has interesting properties that may be studied further.

1 Introduction

Edge detection plays an important role in image processing and analyzing systems. Success in detecting edges may have a great impact on the result of subsequent image processing, e.g. region segmentation, object detection, and may be used in a wide range of applications, from image and video processing to multi/hyper-spectral image analysis. For hyperspectral images, in which channels may provide different or even conflicting information, edge detection becomes more important and essential. Not only it helps to visualize multi-channel images, but also it allows to roughly localize objects.

Edge detection in gray-scale images has been thoroughly studied and is well established. But for color images, especially multi-channel images like hyperspectral images, this topic is much less developed since even defining edges for those images is already a challenge [1]. Two main approaches to detect edges in color/multi-channel images based on monochromatic [2] and vector techniques [3, 4] have been published. The first one detects edges for each individual band, and then combines the results over all bands. The latter treats each pixel in a hyperspectral image as a vector in the spectral domain, and then performs edge detection in this domain. This approach is more efficient than the first one since it does not suffer from the localization variability of edge detection result in the individual channel. Therefore, in the scope of this paper, we only focus on edge detection methods based on vector techniques.

Zenzo [3] proposed a method to extend the edge detection for gray-scale images to multi-channel images. The main idea is to find the direction for a point x for which its vector in the spectral domain has the maximum rate of change. Therefore, the largest eigenvalue of the covariance matrix of the set of partial derivatives is selected as the edge magnitude. Then, a thresholding method could be applied to reveal the edges. However, the problem with this method is how to determine the scale for each channel since the derivatives taken for different channels are often scaled differently. Variations of this approach have been used in [5, 6, 7]. A comparison of these techniques is presented in [1].

This approach can be classified as non-statistical approach since it does not employ the statistical information in spatial domain of the hyperspectral images. One typical problem in analyzing the multi-dimensional images is that the size of samples is very large while the number of samples is small. Therefore, it is necessary to employ available information in both spatial and spectral domain to make use of the properties of different parts, or objects in hyperspectral images.

Trahanias et al. [4] suggested vector-valued ranking operators to detect edges in color images. First, the image is divided into small windows. Then, for each window, the vector-valued data of pixels are ordered increasingly based on the R-ordering algorithm [8]. Finally, ‘‘outliers” are determined and considered as edges. The disadvantage of this method is due to the difficulty in determining window's size. If window's size is set too small, it will cause the problem of discontinuous edges between neighboring windows become more serious. If window's size is too big, some pixels are located far from the others, and therefore, uncorrelated from the others. As a consequence, ordering vector-valued data may not gain a good result.

Huntsberger et al. [9] proposed a statistically based method for edge detection in color images. They considered each pixel as a point in the feature space. A clustering algorithm is applied for a fuzzy segmentation of the image and then outliers of the clusters are considered as edges. Actually, this method performs image segmentation rather than edge detection and often procedures multiple responds for a single edge.

This paper proposes a clustering based method for edge detection in hyperspectral images that could overcome the problem of Huntsberger et al.'s method. Pixel intensity is good for measuring the similarity among pixels, and therefore it is good for the purpose of image segmentation. But it is not good for measuring the abrupt changes to find edges. Pixel gradient value is much more appropriate for that. Therefore, in our approach, we first consider each pixel as a point in the spectral space composed of gradient values in all image bands, instead of intensity values. Then, a clustering algorithm is applied in the spectral space to classify edge and non-edge pixels in the image. Finally, a thresholding strategy similar to the Canny edge detection method [10] is used to refine the results.

The rest of this paper is organized as follows: Section 2 presents the proposed method for edge detection in hyperspectral images. To demonstrate its effectiveness, experimental results and comparison with typical methods are given in Section 3. Conclusion remarks are drawn in Section 4.

2 Clustering based edge detection in hyperspectral images

First, the spatial derivatives of each channel in a hyperspectral images are determined. From [11, 1], it is well-known that the use of convolution masks of 3x3 fixed size pixels is not suitable for the complex problem of determining discontinuities in image functions. Therefore, we use the 2-D Gaussian blur convolution to determine the partial derivatives. Another advantage of using the Gaussian function is that we could smooth the image to reduce the effect of noise, which commonly occurs in hyperspectral images.

After the spatial derivatives of each channel are determined, the gradient magnitude of each pixel is calculated using the hypotenuse functions. Then each pixel can be considered as a point in the spectral space, which includes gradient magnitudes over all channels of the hyperspectral images. The problem of finding edges in the hyperspectral images could be considered as the same problem as classifying points in a spectral space into two classes: edge and non-edge points. We then use a clustering method based on the k-means algorithm for this classification purpose.

One important factor in designing the k-means algorithm is to determine the number of clusters N. Formally, N should be two as we distinguish edges and non-edges. However, in fact, the number of non-edge pixels often dominates the pixel population (from 75% to 95%). Therefore, setting the number of clusters to two often results in losing edges since points in spectral space tend to belong to non-edge clusters rather than edge clusters. In practice, N should be set to be larger than two. In this case, the cluster with the highest population is considered as non-edge cluster. The remaining $N - 1$ clusters are merged together and considered as edge cluster. Apparently, detected edges depends on the number of clusters. Therefore, setting number of clusters should be investigated carefully based on the goal of specific application. Experimental results show that [4, 8] is a reasonable range of N for our application.

After applying the k-means algorithm to classify each point in spectral space into one of N clusters, a combined classifier method proposed by Pavel et al. [12] is applied to remove noise as well as isolated edges. The main idea of this method is to combine the results of two separate classifiers in spectral domain and spatial domain. This combining process is repeated until stable results are archived. In the proposed method, the results of two classifiers are combined using the maximum combination rule.

A thresholding algorithm as in the Canny edge detection method [10] is then applied to refine results from the previous step, i.e. to make the edges thinner. There are two different threshold values in the thresholding algorithm: a lower threshold and a higher threshold. Different from Canny's method, in which threshold values are based on gradient intensity, the proposed threshold values are determined based on the confidence of a pixel belonging to the non-edge cluster. A pixel in the edge cluster is considered as a "true" edge pixel if its confidence to the non-edge cluster is smaller than the low threshold. A pixel is also considered as an edge pixel if it satisfies two criteria: its confidence to the non-edge cluster is in a range between the two thresholds and it has a spatial connection with an already established edge pixel. The remaining pixels are considered as non-edge pixels. Confidence of a pixel belonging to a cluster used in this step is obtained from the clustering step.

The proposed algorithm is briefly described as follows:

Algorithm 1. Edge detection for hyperspectral images

Input: A hyperspectral image I, number of clusters N.

Output: Detected edges of the image.

Step 1:

- Smoothing the hyperspectral image using Gaussian blur convolution.
- Calculating pixel gradient value in each image channel.
- Forming pixel as a point composed of gradient values over all bands.

Step 2: Applying k-means algorithm to classify points into N clusters.

Step 3: Refining the clustering result using the combined classifier method.

Step 4: Selecting the highest population cluster as non-edge cluster, merge other clusters as edge cluster.

Step 5: Applying the thresholding algorithm to refine results from Step 4.

3 Experimental results

3.1 Datasets

To evaluate the performance of the proposed method, a number of hyperspectral datasets from various real world application, e.g. medical, chemical, and remote sensing have been used. The first dataset is a hyperspectral image of Washington DC Mall [13], which contains various types of regions, e.g. roofs, roads, paths, trees, grass, water, and shadows. The second dataset named SEM/EDX contains 8 channels of chemical substances of size 128*128 [12]. This dataset is extremely noisy in both spectral and spatial domains.

The last dataset contains 64 channels of size 1002*1004 of MFISH (Multicolor Fluorescence In Situ Hybridization) [14]. Our goal is to evaluate the performance of edge detection result on extracting nuclei's edges from background. Similar to the second dataset, the MFISH dataset is also noisy. Moreover, the low contrast in intensity between nuclei and background regions makes it difficult to detect nuclei's edges.

Properties of these three datasets are shown in Table 1. Color representation of three datasets using PCA are shown in Figure 1(a), 2(a) and 3(a).

3.2 Results

In order to evaluate the effectiveness of the proposed method, we have compared it with two typical edge detection methods: Zenzo's method [3], a gradient based method, and Huntsberger et al.'s method [9], an intensity clustering based method. Experimental results on these above datasets are shown in Figure 1(b)-(d) - Figure 3(b)-(d). It can be seen from the figures that Huntsberger et al.'s method performs worst: losing edges and creating discontinuous edges. Therefore, we will focus on the performance between Zenzo's method and the proposed method.

For the first dataset, which contains complex images, the two methods produces similar results. But for the second dataset, it can be seen that the proposed method is less effected by noise while still keeps important object's edges in the image.

With the third dataset, the goal is to detect edges of nuclei which are green regions in Figure 3(a). Results in Figure 3(c) and (d) show that, Zenzo's method cannot detect edges of nuclei with low contrast in intensity to the background while the proposed method does. It is because the proposed method makes use of statistical information in spectral space defined by multivariate gradients. Therefore, it works well even with noisy or low contrast images.

4 Conclusions

A clustering based method for edge detection in hyperspectral images is proposed. The proposed method enables the use of multivariate statistical information in multi-dimensional space. Based on pixel gradient values, it also provides a better representation of edges comparing to those based on intensity values, e.g. Huntsberger et al.'s method [9]. As the results, the method reduces the affect of noise and preserves more edge information in the images. Experimental results, though still at preliminary work, show that the proposed method could be used effectively for edge detection in hyperspectral images. More thorough investigation in determining the number of clusters N and the values for the high and low thresholds must be further invested to improve the results.

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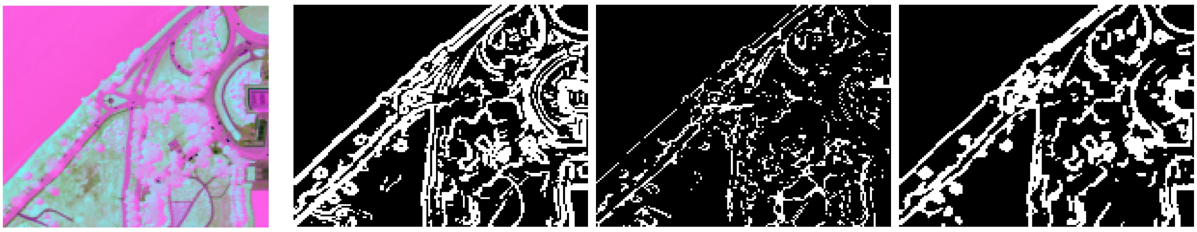
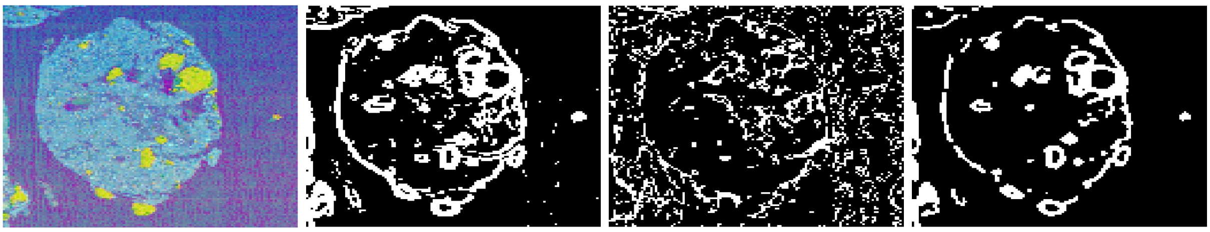
Table 1: Properties of datasets used in experiments

Dataset	No. channels	Spatial Resolution	Response(μm)
DC Mall	191	1280*307	0.40-2.40
SEM/EDX	8	128*128	0.40-1.00
MFISH	64	1002*1004	0.40-0.72



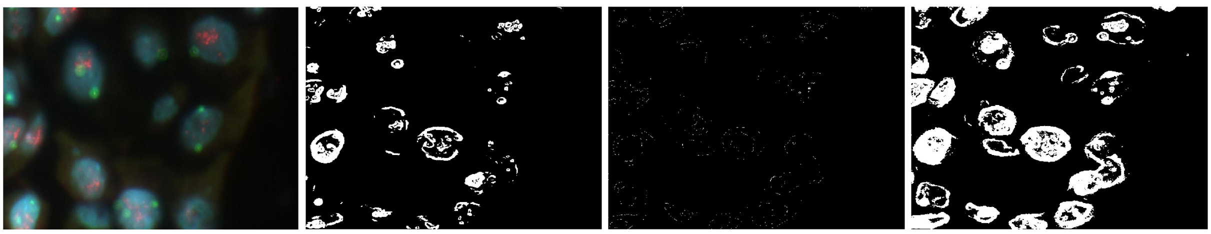
(a) (b) (c) (d)

Figure 1: Edge detection results on the DC Mall dataset. Dataset represented using PCA (a); edge detection results from Zenzo's method (b), Huntsberger et al.'s method (c), and the proposed method (d).



(a) (b) (c) (d)

Figure 2: Edge detection results on the SEM/EDX dataset. Dataset represented using PCA (a); edge detection results from Zenzo's method (b), Huntsberger et al.'s method (c), and the proposed method (d).



(a) (b) (c) (d)

Figure 3: Edge detection results on the MFISH dataset. Dataset represented using PCA (a); edge detection results from Zenzo's method (b), Huntsberger et al.'s method (c), and the proposed method (d).

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