Local Binary Pattern Based Graph Construction for Hyperspectral Image Segmentation

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Abstract. Building highly discriminative graph has an important impact on the quality of graph-based hyperspectral image segmentation. For this purpose, we propose to weight graph edges using Local Binary Pattern (LBP) descriptor that takes into account the texture information of the hyperspectral images. Nodes in the graph embed spectral LBP features computed from the different hyperspectral bands, while edges encode the spatial relationship between these features.

The multiphase level set method is then applied on the constructed graph to segment the image. We validate the proposed method, using Overlapping Score evaluation metric, on several popular hyperspectral images. The results show that our method is very efficient compared to other state-of-the-art one.

Keywords: Hyperspectral image · Graph · LBP · Segmentation · Multiphase level set

1 Introduction

Hyperspectral imaging has recently gained in popularity as a promising optical image acquisition modality, after having been limited to costly remote sensing devices. Hyperspectral sensors can provide a fine sampling of the visible and near infrared spectrum. Hyperspectral data are represented in a three-dimensional image: two spatial dimension and one spectral dimension. Each image pixel corresponds to a high dimensional vector of hundreds of spectral bands captured at this pixel called spectrum. This increased spectral information may, in turn, contribute to a sharper image analysis including hyperspectral image (HSI) segmentation. The aim of HSI segmentation is to partition the image into a set of regions sharing the same properties and characteristics, which may serve as a prior step to many applications such as classification.

Over the past decade, a considerable amount of research has focused on HSI segmentation and classification [2,4,7].

Among proposed methods, one can notice the rise of graph-based algorithms, which have become well-established tools for HSI segmentation problems.

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Graph-based algorithms on the other hand rely upon the construction of a discriminant graph representation.

Moreover, the graph construction is not constrained to usual regular-grid topologies, where each pixel is connected to its adjacent neighbors, but can be adapted to each particular application. One can mention large or complete neighborhood for textured images or Region Adjacency Graphs (RAG) where pixels are replaced by regions or superpixels, and so on.

In a recent study [10] the spatial-spectral structure of weighted graphs has shown its potential for HSI segmentation with the multiphase level set method. In the aforementioned method [10], the weighting of the graph edges was limited to calculating the spectral angle mapper between the image pixels which represent the vertices in the graph.

In this paper, we propose a new metric for edges weighting based on the generalization of the LBP feature on graphs.Our idea is inspired from the Local Binary Pattern (LBP) which was originally proposed by [8] for texture analysis and has later been used in many fields including visual inspection [5], face recognition [6] and motion analysis [1].

LBP is a non-parametric descriptor whose aim is to efficiently summarize the local structures of images. Its advantage over other approaches are its simplicity and effectiveness. This motivated us to propose a novel graph construction based on LBP features. Our aim is to capture the dominant features of the vertices with their neighbors and to encode the local structure around each vertex, before to obtain a small set of the most discriminative LBP-based features for better performance.

2 Preliminaries

In this section we give some basic definitions of important terminologies which are used throughout this paper.

2.1 Graph

A graph $G = (V, E)$ consists of a finite nonempty set of vertices $V = (v_1, ..., v_n)$, and a finite set of edges $E = \{(u, v) \in V \times V | u \sim v\}$ where $\sim$ means that u and v are adjacent vertices, and a weight function, denoted ω: $V \times V \rightarrow [0, 1]$, which represents the weight of each edge in G corresponding to the amount of interaction between two vertices.

In the rest of this paper we denote $\omega(u, v)$ by ω_{uv}. By convention, this function verifies the following properties:

$$\omega_{uv} \begin{cases} \in [0,1] \ \forall (u,v) \in E \\ = 0 \ \forall (u,v) \notin E \\ = \omega_{vu} \text{ symmetry} \end{cases} \tag{1}$$

We now review some operators on weighted graphs [3]. For a given discrete function f which assigns a real value $f(u)$ to each vertex $u \in V$, the weighted discrete partial derivative operator of f applied on an edge $(u,v) \in E$ is:

$$\partial_v f(u) = \sqrt{\omega_{uv}}\left(f(v) - f(u)\right) \tag{2}$$

Based on this definition, two weighted directional difference operators are defined. The external and internal difference operators are respectively:

$$\partial_v^+ f(u) = \sqrt{\omega_{uv}}\left(f(v) - f(u)\right)^+ \tag{3}$$

and

$$\partial_v^- f(u) = -\sqrt{\omega_{uv}}\left(f(v) - f(u)\right)^- \tag{4}$$

with $(x)^+ = \max(0,x)$ and $(x)^- = \min(0,x)$. The weighted gradient of f at vertex u, denoted ∇_w is the vector of all edge directional derivatives:

$$(\nabla_w f)(u) = \left(\partial_v f(u)\right)^T_{(u,v)\in E} \tag{5}$$

The external and the internal weighted gradient operators of f, denoted respectively ∇_w^+ and ∇_w^- are:

$$(\nabla_w^{\pm} f)(u) = \left(\partial_v^{\pm} f(u)\right)^T_{(u,v)\in E} \tag{6}$$

2.2 Local Binary Patterns

The LBP feature has originally been introduced by Ojala et al. [8] for 2D texture analysis. LBP is a non-parametric approach, which accurately summarizes local image structure by comparing central pixels with their neighbors, encoding their relations using a binary code.

Formally, the original LBP operator [8] computes binary codes of image pixels by thresholding the 3×3 neighborhood of each pixel with the center value in a clockwise rotation starting from the top-left one. Pixel neighbors whose intensities are greater or equal to the central pixel's are marked as 1, otherwise as 0. The resulting sequence of 0 and 1 is considered as a 8-digit binary number. Converting this binary sequence into a decimal number we obtain the LBP code of the central pixel.

Figure 1 summarizes the different steps of the LBP calculation. In the context of texture classification using LBP method, the occurrences of the codes (decimal values of LBP codes) in an image are collected in a histogram. The classification is then performed by a simple calculation of distance between histograms.

One limitation of the basic LBP operator is that its small 3×3 neighborhood cannot capture dominant features with large scale structures. To deal with the texture at different scales, the operator was later generalized to use neighborhoods of different sizes [9]. A local neighborhood is defined as a set of sampling points evenly spaced on a circle which is centered at the pixel to be labeled, and the sampling points that do not fall within the pixels are interpolated using bilinear interpolation, thus allowing for any radius and any number of sampling points in the neighborhood.

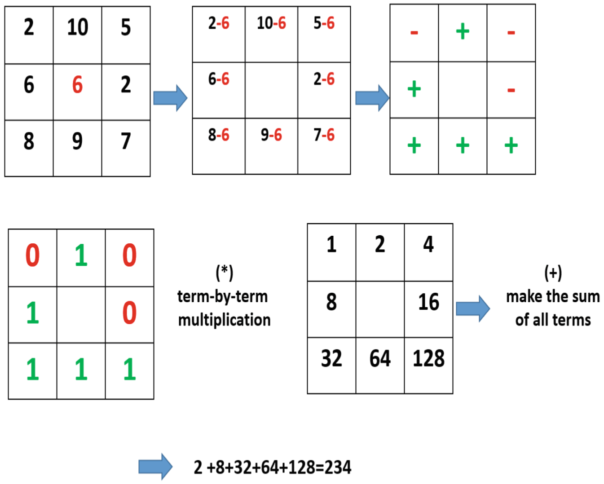

Fig. 1. Overview of LBP computing process

Depending on the scale of the neighborhood used, some regions of interest such as corners or edges can be detected by this descriptor.

Figure 2 shows some examples of the extended LBP operator, where the notation (N, R) denotes a neighborhood of N sampling points on a circle of radius of R.

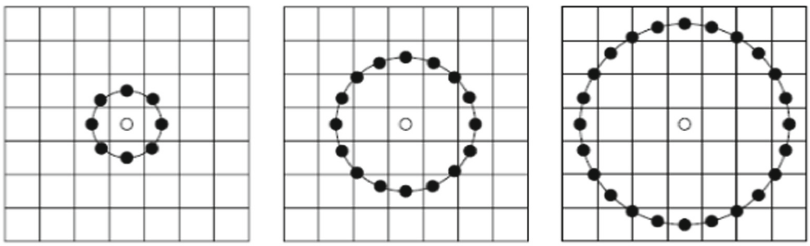

Fig. 2. Examples of the extended LBP operator: the circular (8, 1), (16, 2), and (24, 3) neighborhoods

3 LBP-based Graph Construction

In this section we illustrate the graph construction method using LBP features for a hyperspectral image. The first step consists in representing a HSI (X, Y, Λ), where X, Y and Λ represent respectively the number of lines, columns and spectral bands, as a set of overlapping patches $\{P_i, i = 1...m\}$, each patch P_i being extracted around a representative pixel $p_i = (x_i, y_i, \lambda_i)^t$.

The m pixels of the image are the centers of m patches of radius R. Each pixel in the HSI is represented by a vertex in the graph connected to the 4 nearest spatial vertices with a weighted edge. For each representative pixel p_i, we compute a LBP code over each HSI band λ as follows:

$$LBP_{\lambda_i}(p_i) = \sum_{n=0}^{N-1} sign(S_{\lambda_i}(n) - S_{\lambda_i}(c)) \times 2^n \tag{7}$$

where $S_{\lambda_i}(c)$ represent the spectral value on the band λ_i of the central pixel, $S_{\lambda_i}(n)$ represent the spectral value on the same band of its neighbors and N represent the total number of pixel in a Patch P_i, and sign(x) is a sign function defined by $sign(x) = 1$ where $x \geq 0$ and 0 otherwise. So, the $LBP(p_i)$ (8) is a vector feature which can be seen as a serial concatenation of standard LBP codes computed over each HSI band separately (7).

$$LBP(p_i) = \sum_{k=0}^{\Lambda} LBP_{\lambda_k}(p_i) \times 2^{k \times N} \tag{8}$$

Once these LBP vector codes are calculated for each representative pixel (i.e vertex in the constructed graph), the Hamming distance is used to compute the weights of the graph edges between each vertices pair (u,v). This is performed by applying the XOR operator between the binary chains of the LBP vector codes of corresponding vertices, which gives as results the number of positions at which the binary chains are different. Figure 3 and Eq. (9) explains the Hamming distance calculation between the two LBP binary chains of u and v, where $\bigoplus$ means the XOR operator.

$$d_{Hamming}(u, v) = \sum_{i=0}^{N \times \Lambda} (LBP_{binary_u}(i) \bigoplus LBP_{binary_v}(i)) \tag{9}$$

In this paper, we proposed to study the distribution of the Hamming distance between LBP binary codes for encoding the actual changes of pixels values.

A normalization step is finally applied to set all edge values within the $[0, 1]$ interval. In this paper, and without being exhaustive, we used the following normalization (10), where σ represents the standard deviation calculated over all Hamming distances:

$$\omega(u, v) = exp(-\frac{d_{Hamming}(u, v)^2}{\sigma^2}) \tag{10}$$

4 HSI Segmentation

After HSI graph construction and calculating W affinity matrix which represents the weight of all the edges in the graph, we apply the multiphase level set graph based method [10] to partition the graph into n regions and deduce HSI segmentation.

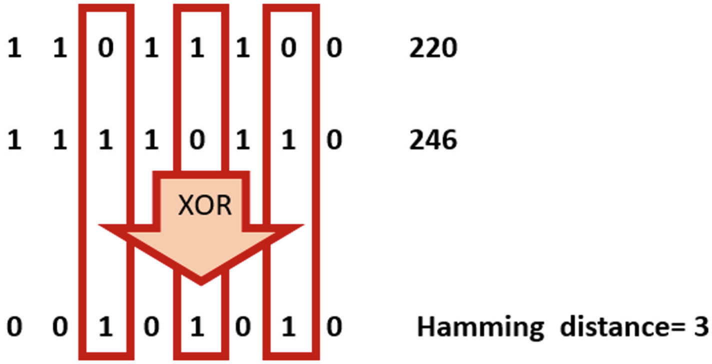

Fig. 3. Hamming distance calculation between LBP codes

We first initialize the n level set functions ϕ_i by n initial contours on the image, then we compute the averages in each region composed by the superposition of these contours and we calculate the speed propagation function F_n to solve the curve evolution equation as follows:

$$\frac{\partial \phi_n(u,t)}{\partial t} = \begin{cases} F_n(u,t)\ ||(\nabla_\omega^+ \phi_n)(u,t)||, \text{ if } F_n(u,t) > 0 \\ F_n(u,t)\ ||(\nabla_\omega^- \phi_n)(u,t)||, \text{ if } F_n(u,t) < 0 \\ 0, \text{ otherwise} \end{cases} \tag{11}$$

where $(\nabla_\omega^+ \phi_n)(u,t)$ and $(\nabla_\omega^- \phi_n)(u,t)$ are the external and internal operators of weighted gradients. Based on Eqs. (3), (4) and (6), the external and internal operators of weighted gradients of ϕ_n can be defined by:

$$(\nabla_\omega^\pm \phi_n)(u) = \pm\sqrt{\omega_{uv}}((\phi_n(v) - \phi_n(u))^\pm)^T_{(u,v)\in E} \tag{12}$$

Finally we iterate the last three steps. We show in Fig. 4 an example of initial contours using the four-phase (with two level set functions) models.

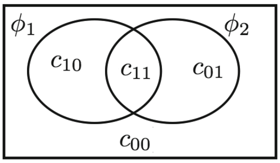

Fig. 4. Two contours split the image into 4 regions: $c_{11} = \{\phi_1 > 0, \phi_2 > 0\}, c_{10} = \{\phi_1 > 0, \phi_2 < 0\}, c_{01} = \{\phi_1 < 0, \phi_2 > 0\}, c_{00} = \{\phi_1 < 0, \phi_2 < 0\}$

5 Experiments

In this section, we evaluate the proposed LBP-based graph construction method for HSI segmentation on some popular HSIs: the Pavia University, the Indian Pines and the Salinas hyperspectral images.

The Pavia University image was captured during a flight campaign over Pavia university in northern Italy and it was acquired by the ROSIS-03 optical sensor. This image contains 610×340 pixels on 103 spectral bands with a spatial resolution of 1.3 m/pixel. The AVIRIS Indian Pine image, which was recorded by the AVIRIS sensor contains 145×145 pixels with 200 spectral reflectance bands. The third image is the AVIRIS Salinas scene which was recorded by the 224-band AVIRIS sensor over Salinas Valley, California. This image comprises 512×217 pixels with a high spatial resolution of 3.7 m/pixel.

We evaluated the proposed LBP-based graph construction method with a patch size 7×7 corresponding to a circular (24, 3) neighborhoods (Fig. 2). We compared our construction graph approach with the 4-neighborhood graph construction using the multiphase level set segmentation proposed in [10].

Figure 5 represent a zoom on some different regions taken from our HSIs and the segmentation results in this regions presented in line-wise, from top to bottom, line 1 and 4 shows the RGB original images, line 2 and 5 shows the segmentation results using the four-phase model with the proposed LBP-based graph construction, when line 3 and 6 show the segmentation results with the aforementioned method [10].

From this visual comparison of our results with the other method, we can see that our proposed method can obtain more meaningful region with accurate boundary. It can be observed that our method can well segment the texture images (the meadows, the brick) and it has high discriminative power to detect objects from different backgrounds.

To evaluate the results obtained for HSIs segmentation we compute the Overlapping Score (OS) to compare the segmented image S and the ground truth G. The OS metric is defined by:

$$OS = \frac{|S \cap G|}{min(|S|, |G|)} \tag{13}$$

Table 1. Overlapping Score (OS) for the Pavia University, Indian Pines and Salinas images segmentation with both graph construction methods (four-phase segmentation)

HSI	Method	
	4-neighborhood graph construction	LBP-based graph construction
Pavia University	0.8387	**0.9102**
Indian Pines	0.8563	**0.9275**
Salinas	0.8392	**0.9134**

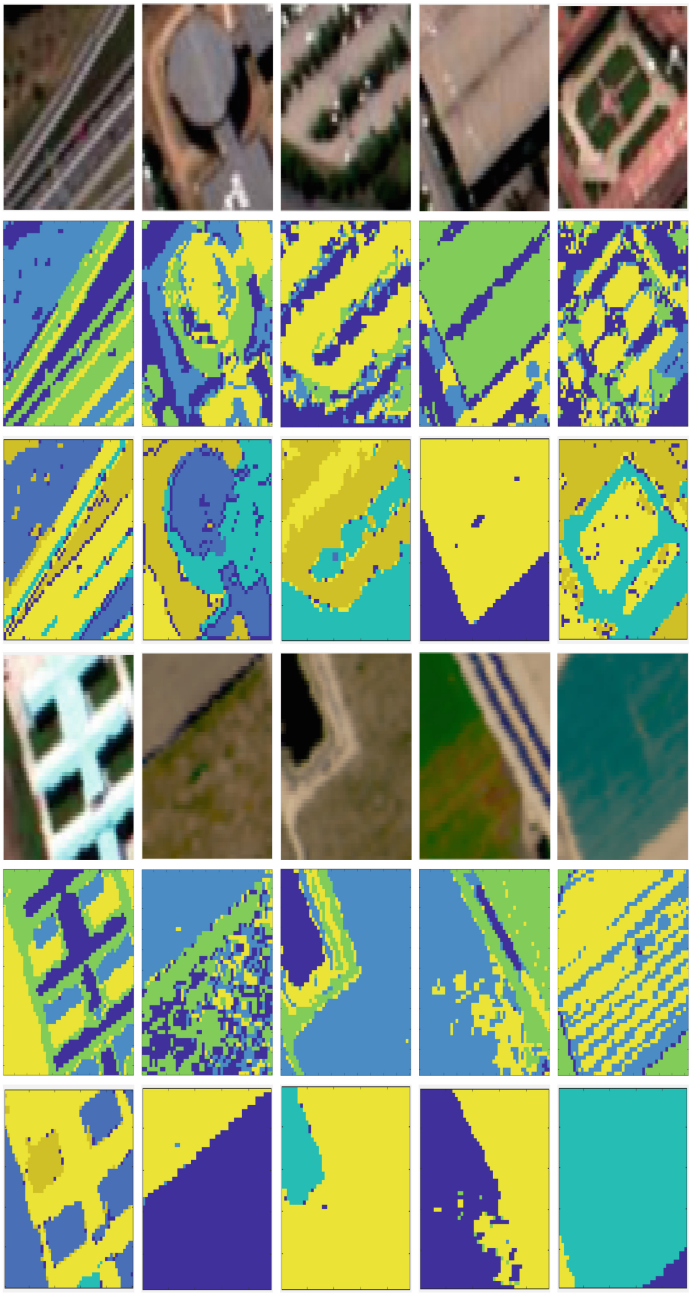

Fig. 5. Visual comparison of our results with the other method (Lines (1 and 4) RGB regions of interest extracted from Pavia University, Indian Pines and Salinas images, lines (2 and 5) the four-phase level set segmentation results on LBP-based graph construction, lines (3 and 6) the four-phase level set segmentation on 4-neighborhood graph construction)

Evaluation of segmentation results is given in Table 1, with the best results highlighted in bold for each measurement. It is obvious to see that the proposed LBP-base graph construction method ranks the first place compared with the other method.

6 Conclusion

In this paper, we propose a new method based on the LBP descriptor to construct the graph for hyperspectral image segmentation. The proposed method is invariant to uneven light conditions and noise benefiting from the usage of LBP patches. The proposed method is evaluated by extensive experiments on three popular HSI, and is quantitatively compared with some other standard algorithms. The experimental results have shown the potential of our method and its efficiency in HSI segmentation. Our future work will focus on the effects of the LBP patch size on the segmentation performance of our proposed method, we will also analyze how it varies with respect to the number of sample points in the LBP patch.

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