

Multispectral image segmentation using localized spectral binarization

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Abstract. This paper proposes a new feature extraction method for multispectral image segmentation based in Localized Spectral Binarization (LSB). In contrast with the standard image operation, which is applied with traditional image, LSB is computed on a single pixel with numerous bands. The proposed algorithm calculates differences of spectra locally on same pixel's coordinate in different bands of the multispectral image. The difference value is converted into binary by breaking the difference values into two directions, which are the positive and negative value then the differences are thresholded to form a binary codeword. A binomial factor is assigned to these codewords to form another unique value. These values are then grouped to construct the LSB feature image where is used in the image segmentation. LANDSAT multispectral images are used in the experiment to evaluate the segmentation and classification accuracy of the proposed LSB in terms of pixel-wise image segmentation. The result shows that LSB feature outperforms the spectral feature.

1. Introduction

Segmentation is process of dividing an image space into some none overlying meaningful homogeneous regions [1]. Multispectral images cover more information than single band images. One of the vital approaches of information extraction, is the multispectral image segmentation. Object-based image analysis secret to success in accurateness is dependent on the quality of the image segmentation. Commonly, multispectral has three to seven bands. To achieve a higher accurate image segmentation and classification result, the extra information from multispectral will significantly help with the result. Meanwhile, mishandling of the extra band information can cause to low performance of image segmentation. Grey value thresholding and pixel classification are the two popular approaches for image segmentation in remote sensing process. In image thresholding [2], a set of thresholds T is searched so that all pixels with gray values in range constitute the i th region type. Homogeneous regions are determined by clustering the feature space of multiple image bands in pixel allocation. Pixel classification and thresholding methods can be either local or global. Pixel classification-based segmentation is frequently applied because of each pixel in multispectral image is represented by a set of values.

Histogram-based and cluster based methods are divided into two based on pixel classification-based segmentation. The histogram-based method assumes that homogeneous regions in the image correspond to modes of image histogram. They are based on the spectral feature space [3]. Cluster-based segmentation methods assume that interesting structures in the image form clusters in the band domain.



The basic idea behind histogram and cluster-based segmentation is that image pixels are processed as general data samples in the feature space. The performance of cluster-based segmentation method depends on the feature of the each pixel. Standard cluster-based method for multispectral image applies the spectral information as the feature of the each pixel. However this information is not enough and often leads to misclassification. In order to increase the feature information, extra information needs to be extracted from the spectral.

In this paper, we propose a novel feature extraction of spectral information based on Localized Spectral Binarization (LSB) [4]. LSB is based on the local neighborhood difference between the surrounding and the central pixels in a all bands. The remainder of this paper is organized as follows: in Section 2, related work is presented; in Section 3, detailed algorithm to implement LSB in multispectral image segmentation is presented; experimental evaluations are described in Section 4 and finally conclusions and future works are given in Section 5.

2. Related Work

2.1. Local Binary Pattern

The detail explanation about LBP [5] algorithm using 3x3 neighborhoods is shown in Figure 1. First, the neighboring pixels of the 3x3 neighborhood are extracted. For each 3x3 window of an image, neighborhood differences which are the centralized difference $v(n)$ are calculated. Then the $v(n)$ are thresholded against zero in order to convert the difference values into 8-bit binary codeword. A binomial factor of 2 is assigned for each binary code to transform the codeword into a unique LBP number that represents the texture unit of the 3x3 neighborhood. This LBP value is a decimal value between 0 and 255 resulting from the 8-bit binary code. Next, a histogram is constructed with 256 dimensions using the LBP values and the histogram denotes the distribution of the CND values. Finally, the texture descriptor is obtained from the histogram.

The extremely simple computations for constructing the LBP make it very fast in extracting image feature. The performance of LBP is also similar with other local texture descriptors such as combined neighborhood difference (CND) [9] and local neighbor differences (LND) [6].

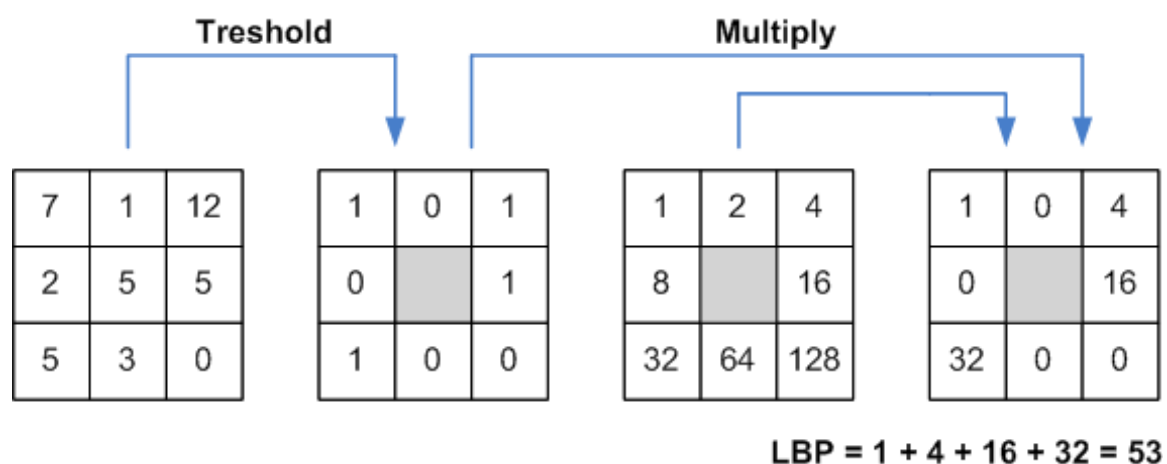


Figure 1. Figure shows a LBP example.

3. Proposed Method

3.1. The Localized Spectral Binarization Histogram

Multispectral image uses more than one band to represent an image. Each band acquires one digital image in a small band of visible spectra, ranging 0.4 μm to 0.7 μm , called red-green-blue (RGB) region, and going to infra-red wavelengths of 0.7 μm to 10 μm or more, classified as Near InfraRed (NIR), Middle InfraRed (MIR) and Far InfraRed (FIR) or Thermal [7].

Each pixels of a multispectral image contains several values depending on the number of the band. To increase the significant information, LSB feature is extracted from each band for each pixel. The multispectral images can be converted into the feature space $F(x,y,c)$ using LSB using several steps. First, the pixel value from each band of the multispectral image is gathered to form a 1D data $p(a)$, $a=1, 2, \dots, n$ where n is the number of band in the multispectral image. Then, $p(a)$ is divided into the center group $c(a)$, $a=1, 2, \dots, n$ and the neighborhood group $x(a,b)$, $a=1, 2, \dots, n$, $b=1, 2, \dots, n-1$ as follows:

$$\begin{aligned} c(a) &= p(a) & a &= 1, 2, \dots, n \\ x(a,b) &= p\{1 + (a + b - 1) \bmod n\}, & b &= 1, 2, \dots, n-1 \end{aligned} \quad (1)$$

Then the differences between $x(a,b)$ and $c(a)$ is calculated and the values are thresholded against 0 as follows:

$$T(a,b) = \begin{cases} 1, & \text{if } \{x(a,b) - c(a)\} > 0 \\ 0, & \text{otherwise} \end{cases}, \quad (2)$$

$a = 1, 2, \dots, n, \quad b = 1, 2, \dots, n-1$

$T(a,b)$ can be seen as an 2D array of binary code. By handling each row in $T(a,b)$ as a $n-1$ bit of binary codeword, it is possible to transform (3) into a unique LSB number for each band. It is done by assigning a binomial factor H for each $T(a,b)$, given by

$$f(a) = \sum_{b=1}^{n-1} T(a,b) H^{b-1}, \quad a = 1, 2, \dots, n \quad (3)$$

$f(a)$ is then saved in the feature image $F(x,y,a)$. If the size of the multispectral image is $M \times N$, $x=1, 2, \dots, M$, $y=1, 2, \dots, N$ and $a=1, 2, \dots, n$. This process is repeated to each pixel of the multispectral image. $F(x,y,a)$ is then used as the feature in the segmentation of the multispectral image. In the feature image $F(x,y,a)$, each pixels have a set of LSB values. The number of LSB code each pixel has is the same as the number of band of the multispectral image.

3.2. The Segmentation

The K-Means algorithm [8] is used as the clustering method in the unsupervised segmentation of the multispectral image. K-Means algorithm classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. Given a set of points $x=(\)$, where each point is a n -dimensional real vector. The points are clustered around centroids which are obtained by minimizing the within-cluster sum of squares

$$V = \sum_{i=1}^k \sum_{x_j \in S_i} (x_j - \mu_i)^2 \quad (4)$$

Where there are k clusters, $i=1,2, \dots, k$ and μ_i is the centroids or mean point of all of the points. To segment the multispectral image, pixel values in $F(x,y,a)$ feature image are grouped into a group of points $x=(\cdot)$, where each LSB values of each pixel in $F(x,y,a)$ is assigned as the n-dimensional vector of the points.

4. Experimental Results

To evaluate the performance of the LSB in segmentation of multispectral images, the classification and segmentation of two LANDSAT 7 multispectral images of Rio Janeiro. The images of Rio Janeiro in the RGB band can be seen in Figure 2. We can judge the segmentation performance by scrutinizing the clarity of the segmentation result. The precision of the segmentation can also be assessed using classification accuracy, which can be calculated as follows:

$$\text{accuracy}(\%) = \frac{\text{no. of correctly classified pixels}}{\text{no. of pixels in each class}} \quad (5)$$



Figure 2. Figure shows Pixel Rio Janeiro

The Rio Janeiro image contains seven bands and the binomial factor H assigned for Rio Janeiro image is 2. The pixels are grouped into a set of points in order to perform the K-mean clustering with Euclidean distance. The pixels in the image are clustered into three main classes (K=3) namely, water, build-up and vegetation. The segmentation performance using LSB feature is compared with that of segmentation using spectral feature. The results of the segmentation of Rio Janeiro multispectral image using LSB feature and spectral feature are shown in Figure 3. The classification accuracy result can be seen in Table 1.

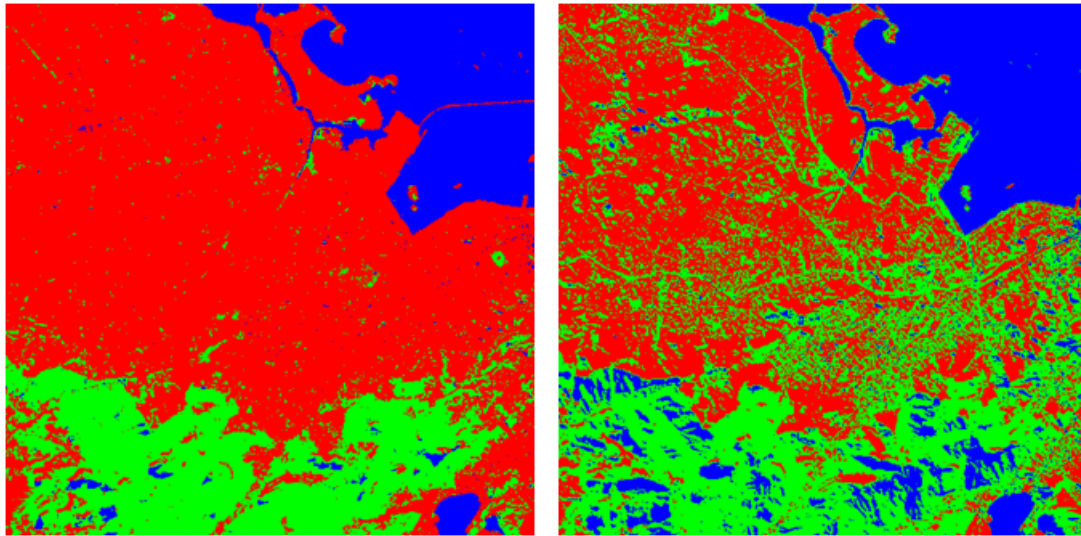


Figure 3. The segmentation result of Rio Janeiro images

Table 1. The classification accuracies

Method	Water	Build-up	Vegetation	Average
LSB	95.72	89.10	85.12	89.98
Spectral	95.17	70.03	2.22	55.81

From the segmentation results, one can see that the segmentation using LSB feature distinctly clustered each pixel into three classes compared to that of spectral feature. The bridges are always misclassified as water. However, LSB manages to perfectly classify all of the bridges. The color of the vegetation area is similar to that of water area. From the result, we can see that the segmentation using spectral feature misclassified these two areas. On the contrary, LSB manages to classify these two areas almost perfectly. From the classification accuracy results, we can see that LSB perform consistently in the classification with average accuracy of 89.98%. The classification accuracy using spectral feature is unstable since a lot of vegetation areas are misclassified as water areas. This misclassification causes low average classification accuracy, which is 55.81%.

5. Conclusion

In this paper, we propose a novel feature extraction method for multispectral image based on the LSB. The LSB is calculated on single pixel with various bands. The result of segmentation using LSB feature shows greater result compared to that of using spectral feature. LSB feature also achieves high segmentation accuracy compared to those of spectral feature. For the future works, we would like to implement the LSB algorithm in the hyperspectral image analysis such as target detection. Hyperspectral image contains more than 200 dimensions, and the feature extraction of extremely high dimensional image is not an easy task.

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