1D 통합된 근접차이에 기반한 자율적인 다중분광 영상 분할

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Unsupervised Multispectral Image Segmentation Based on 1D Combined Neighborhood Differences

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Abstract

This paper proposes a novel feature extraction method for unsupervised multispectral image segmentation based in one dimensional combined neighborhood differences (1D CND). In contrast with the original CND, which is applied with traditional image, 1D CND is computed on a single pixel with various bands. The proposed algorithm utilizes the sign of differences between bands of the pixel. The difference values are thresholded to form a binary codeword. A binomial factor is assigned to these codeword to form another unique value. These values are then grouped to construct the 1D CND feature image where is used in the unsupervised image segmentation. Various experiments using two LANDSAT multispectral images have been performed to evaluate the segmentation and classification accuracy of the proposed method. The result shows that 1D CND feature outperforms the spectral feature, with average classification accuracy of 87.55% whereas that of spectral feature is 55.81%.

Keyword: unsupervised image segmentation, multispectral image, remote sensing, combined neighborhood differences

1. INTRODUCTION

Segmentation is a process of partitioning an image space into some nonoverlapping meaningful homogeneous regions [1]. Multispectral image segmentation is one of the important approaches of information extraction. The success of object-based image analysis is dependent on the quality of the image segmentation. However, multispectral images contain more information than single-band (gray) images. Usually, multispectral image has three to seven bands. If the extra information can be utilized efficiently, it can lead to more accurate image segmentation and classification result. On the other hand, mishandling of this extra band information can lead to low performance of image segmentation.

Two popular approaches for image segmentation in remote sensing are gray value thresholding and pixel classification. In image thresholding [2], a set of thresholds T is searched so that all pixels with gray values in range $[T_i, T_{i+1})$ constitute the ith region type. In the pixel classification, homogeneous regions are determined by clustering the feature space of multiple image bands. Both thresholding and pixel classification methods can be either local or global. Because each pixel in multispectral image is represented by a set of values (pixel values in each band), pixel classification-based segmentation is frequently applied.

Pixel classification-based segmentation can be divided into two approaches such as histogram-based and cluster based methods. They are based on the spectral feature space [3]. The histogram-based method assumes that homogeneous regions in the image correspond to modes of image histogram. 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 Combined Neighborhood Differences (CND) [4]. CND is based on the local neighborhood difference in an image and uses 2D image space in its construction. A new algorithm is presented in order to implement CND on a 1D data, as in the spectral.

The remainder of this paper is organized as follows: in Section 2, related work is presented; in Section 3, detailed algorithm to implement 1D CND in multispectral image

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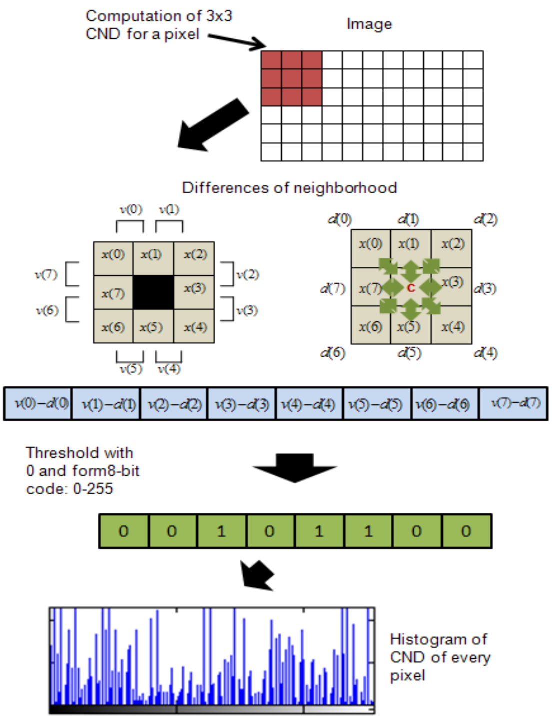
segmentation is presented; experimental evaluations are described in Section 4 and finally conclusions and future works are given in Section 5.

2. RELATED WORK

2.1. Combined Neighborhood Difference

The detail explanation about CND algorithm using 3x3 neighborhoods is shown in Fig. 1. First, the neighboring pixels of the 3x3 neighborhood are extracted. For each 3x3 window of an image, two neighborhood differences which are the centralized difference $v(n)$ and surrounding neighborhood difference $d(n)$ are calculated. Then the differences between $v(n)$ and $d(n)$ 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 CND number that represents the texture unit of the 3x3 neighborhood. This CND 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 CND values and the histogram denotes the distribution of the CND values. Finally, the texture descriptor is obtained from the histogram.



<Fig. 1> The CND algorithm

The extremely simple computations for constructing the CND make it very fast in extracting image feature. The performance of CND is also better than those of similar local texture descriptors such as local binary patterns (LBP) [5] and local neighbor differences (LND) [6].

3. PROPOSED METHOD

3.1. The Spectral Feature Extraction

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 feature information, 1D CND feature is extracted from each band for each pixel. The algorithm to perform 1D CND on the multispectral image is shown in Fig. 3. The multispectral images can be converted into the feature space $F(x,y,c)$ using 1D CND 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,…, n where n is the number of band in the multispectral image. Then, $p(a)$ in divided into the center group $c(a)$, a=1, 2,…, n and the neighborhood group $x(a,b)$, a=1, 2, …, n, b=1, 2,…, n-1 as follows:

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

From the formula we can see that the size of $c(a)$ is 1 by n whereas the size of $x(a,b)$ is n by n-1. Same as the original CND algorithm, the centralized difference $d(a,b)$ and neighboring difference $v(a,b)$ are calculated using the following formula:

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

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

$$T(a,b) = \begin{cases} 1, \text{ if } \{v(a,b) - d(a,b)\} > 0 \\ 0, \qquad\qquad \text{otherwise} \end{cases}, \qquad (3)$$
$$a = 1,2,\dots,n,\ b = 1,2,\dots,n-1$$

$T(a,b)$ 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 1D CND number for each band. It is done by assigning a binomial factor H for each $T(a,b)$, given by

$$f(a) = \sum_{b=1}^{n-1} T(a,b) H^{b-1},\ a = 1,2,\dots,n \qquad (4)$$

$f(a)$ is then saved in the feature image $F(x,y,a)$ as shown in Fig. 3. If the size of the multispectral image is MxN, x=1, 2, …, M, y=1, 2,…, N and a=1, 2,…, 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 1D CND values. The number of 1D CND 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=($x_1, x_2, \ldots, x_d$), where each point is a n-dimensional real vector. The points are clustered around centroids $\mu_i \forall i = 1, \ldots, k$ which are obtained by minimizing the within-cluster sum of squares

$$V = \sum_{i=1}^{k} \sum_{x_j \in S_i} \left(x_j - \mu_i \right)^2 \qquad (5)$$

where there are k clusters, S_i, i=1,2, …, k and μ_i is the centroids or mean point of all of the points $x_j \in S_i$.

To segment the multispectral image, pixel values in $F(x,y,a)$ feature image are grouped into a group of points x=($x_1, x_2, \ldots, x_d$), where each 1D CND values of each pixel in $F(x,y,a)$ is assigned as the n-dimensional vector of the points.

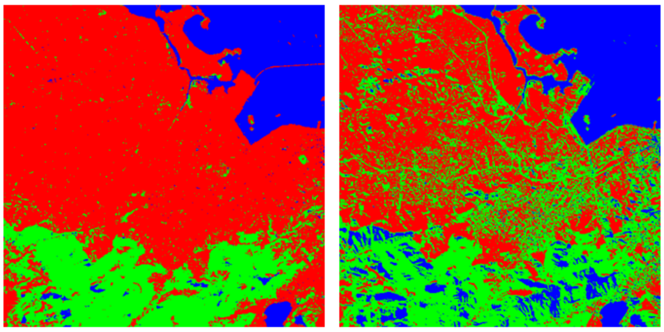
4. EXPERIMENTAL RESULTS

<Fig. 4> Rio Janeiro (left) and Seoul (right) images in RGB band

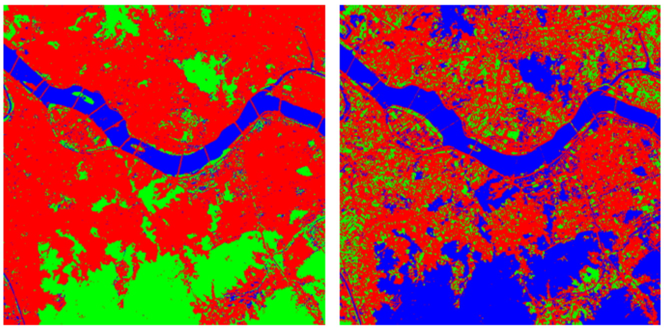
To evaluate the performance of the 1D CND in segmentation of multispectral images, the classification and segmentation of two LANDSAT 7 multispectral images of Rio Janeiro and a partial of Seoul have been conducted. The images of Rio Janeiro and Seoul in the RGB band can be seen in Fig. 4. We can judge 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:

$$\text{accuracy}(\%) = \frac{\text{no. of correctly classified pixels}}{\text{no. of pixels in each class}} \qquad (6)$$

The Rio Janeiro image contains seven bands while the Seoul image contains six bands. The binomial factor H assigned for Rio Janeiro image is 2 while for Seoul image is 3. 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 1D CND feature is compared with that of segmentation using spectral feature. The results of the segmentation of Rio Janeiro multispectral image using 1D CND feature and spectral feature are shown in Fig. 5, while the segmentation of Seoul multispectral image using 1D CND feature and spectral feature are shown in Fig. 6. The classification accuracy result can be seen in Table 1.



<Fig. 5> The segmentaition result of Rio Janeiro images



<Fig. 6> The segmentaition result of Seoul images

<**Table 1**> The classification accuracies

Method	Water	Build-up	Vegetation	Average
CND	90.72	88.80	83.12	87.55
Spectral	95.17	70.03	2.22	55.81

From the segmentation results, one can see that the segmentation using 1D CND feature distinctly clustered each pixel into three classes compared to that of spectral feature. The bridges are always misclassified as water. However, 1D CND 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, 1D CND manages to classify these two areas almost perfectly. From the classification accuracy results, we can see that 1D CND perform consistently in the classification with average accuracy of 87.55%. 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 AND FUTURE WORKS

In this paper, we propose a novel feature extraction method for multispectral image based on the 1D CND. The 1D CND is calculated on single pixel with various bands. The result of segmentation using CND feature shows excellent result compared to that of using spectral feature. 1D CND feature also achieves high segmentation accuracy compared to those of spectral feature.

For the future works, we would like to implement the CND algorithm in the hyperspectral image analysis. Hyperspectral image contains more than 200 dimensions, and the feature extraction of extremely high dimensional image is not an easy task. A new CND algorithm will be studied to extract the feature from high dimensional hyperspectral image.

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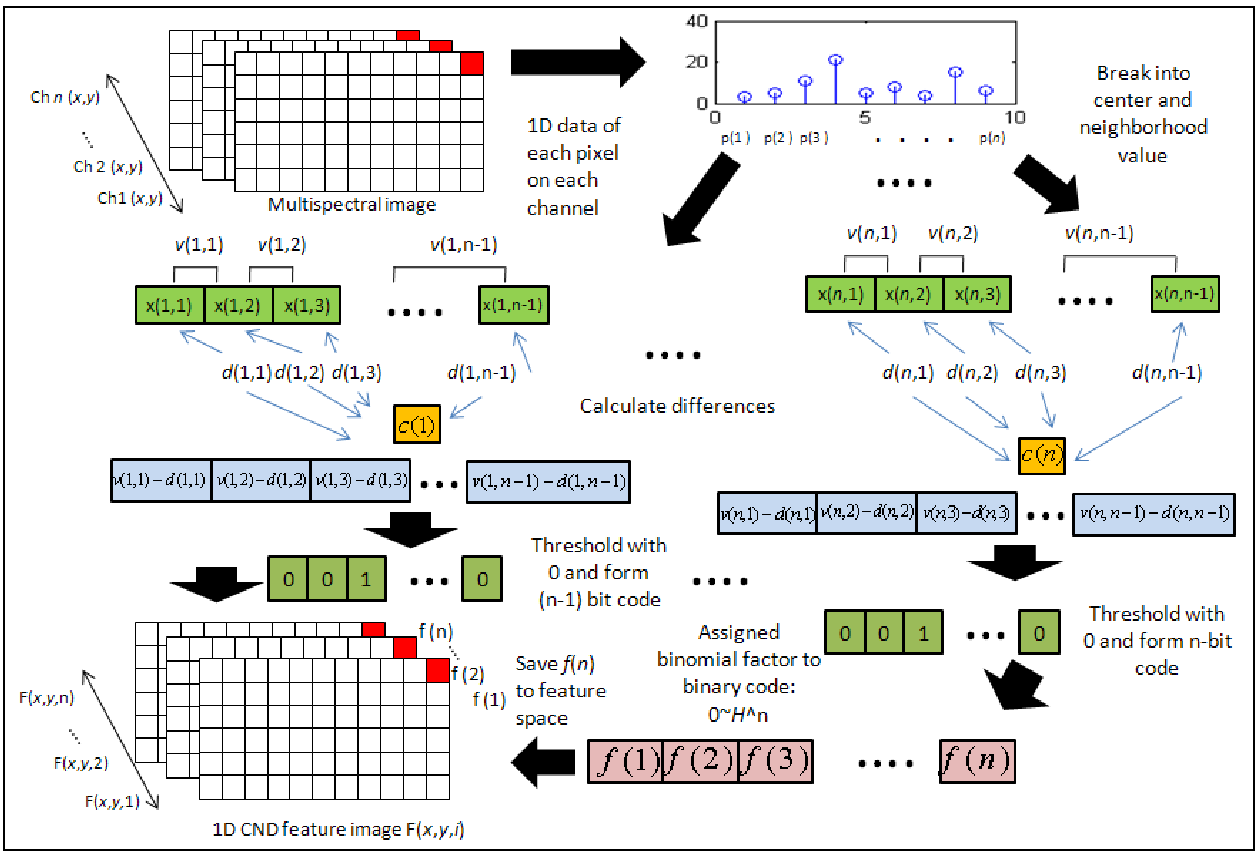

<Fig. 3> The 1D CND algorithm for multispectral image