A Texture Segmentation Using Modified Hill-Climbing Approach

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Abstract— Image segmentation is crucial to object-oriented remote sensing imagery analysis. In this paper, a newly modified texture segmentation algorithm is proposed using spectral, shape and intensity features. This algorithm is a robust technique that can be applied directly to the color images. The image is preprocessed using Adaptive Switching Median Filter, which removes the impulse noises and keeping the fine details of the image intact in the most efficient manner. Also, the preprocessed image is smoothened using morphological operators, which reduces the false detection of abnormal cells. Then, the preprocessed image is transformed into HSV (Hue, Saturation and value) color space representation in order to analyze and establish a color contrast gradient. The multiscale morphological gradient in the intensity channel of the preprocessed image is obtained and multiplied with the color contrast gradient. The shape feature is extracted from the preprocessed image based on the descriptors such as compactness, convexness, rectangularity and eccentricity, moment invariants. Based on these spectral, shape and intensity features, markers are extracted for this image and given as input to the watershed algorithm which uses a Hill-Climbing approach to identify and label the neighborhood pixels. This algorithm may reduce the computational complexity by avoiding the process of computing lower-complete image.

Index Terms— Color contrast gradient, multiscale morphological gradient, shape feature, marker, texture segmentation.

1 INTRODUCTION

Image Processing is a technique to enhance the raw images received from cameras/sensors placed on satellites, space probes and aircrafts or pictures taken in normal day-to-day life for various applications. Various techniques have been developed in Image Processing during the last four to five decades. Most of the techniques are developed for enhancing images obtained from unmanned space crafts, space probes and military reconnaissance flights. Image Processing systems are becoming popular due to easy availability of powerful personnel computers, large size memory devices, graphics software etc. The term digital image processing generally refers to processing of a two-dimensional picture by a digital computer. The principle advantage of Digital Image Processing methods is its versatility, repeatability and the preservation of original data precision.

Image segmentation is the process that subdivides an image into its constituent parts or objects. The level to which this subdivision is carried out depends on the problem being solved, i.e., the segmentation should stop when the objects of interest in an application have been isolated e.g., in autonomous air-to-ground target acquisition, suppose our interest lies in identifying vehicles on a road, the first step is to segment the road from the image and then to segment the contents of the road down to potential vehicles. Image thresholding techniques are used for image segmentation.

In the Earth observation field, object-oriented image analysis has been an important method for handling high resolution remote sensing data. Compared with pixel-based classification, the object-oriented method has many advantages [1]. It overcomes the salt-and-pepper noise that is inherent in pixel-based classification and extracts from regions the features that are more meaningful and important for interpretation. Moreover, the result of object-oriented analysis can be easily integrated with Geographical Information System for further applications.

It is well known that image segmentation is the basis of object-oriented image analysis and is still an intractable problem. According to the different features, the segmentation techniques can be classified into the following three types: spectral segmentation, texture segmentation, and spectral–texture combined segmentation. Most of the spectral segmentation methods [2], [3], [4] attempt to find homogeneous spectral regions and have good performance on photographic images of simple scenarios. As for high-resolution images, which contain more regions with spectral variance and texture homogeneity, the researchers [5], [6], [7], [8] have tried texture segmentation methods, which work well on synthetic compositions of textures. However, most of the texture features are the characteristic descriptions of the given windows and are not sensitive to object edges. Thus, it is difficult to find the real object boundaries in high-resolution images by using only texture features. Spectral–texture combined segmentation [9], [10], [11] may be a good solution for high-resolution images.

2 Existing System

Chen *et al.* [9] presented an algorithm in which the image was segmented by spectral and texture features independently at first and, then, the "max" operator was used to obtain overall segmentation by combining the interim results. Deng and Manjunath [10] proposed the JSEG algorithm for solving this problem, in which the spectra of the image were quantized to the spatial texture *J*-image, and the result was achieved using region-growing algorithms to segment the *J*-image. Akçay and Aksoy [11] used multiscale morphological operations to extract texture information, with the meaningful segments being obtained by maximizing the measure of spectral homogeneity and neighborhood connectivity. Nan Li et al. [12] proposed a texture-preceded segmentation algorithm, in which the regions are labelled by texture clustering. A model of distance space is used, which combines spectral, texture, and shape features, to describe objects in a semantically consistent way. To detect the real edges a distance space model is used, which combines spectral, shape, and texture features. Then, this distance measure is applied to the graph models Region Adjacency Graph (RAG) and Nearest Neighbor Graph (NNG) to find the optimal merging sequence by minimal distance among the entire region. The final segmentation results can be obtained by merging the optimal nodes in NNG and RAG iteratively. During the merging, texture clustering interacts with optimal sequence merging, which refines the real edges of the texture region gradually.

Despite the fact that many algorithms deliver good performances by combining different features in segmentation, there are still several problems that have not yet been solved satisfactorily. First, the over-segmentation: It results in a number of small regions hardly to analyze; Second, sensitivity to noise; Third, poor detection of significant areas with low contrast boundaries; Fourth, poor detection of thin structures; Fifth, size and scale of the objects are not dealt with in texture segmentation; Sixth, it is difficult to apply texture segmentation directly to the color images due to the difficulty in getting gradient images. In this paper, a newly modified texture segmentation algorithm is proposed for textured image segmentation which is a solution to the above problems.

3 Proposed System

In the proposed system, the image is pre-processed using Adaptive Switching Median Filter and smoothened using morphological operators, which makes possible the perfect removal of impulse noises and keep the fine details of the image intact in the most efficient manner. Then, the preprocessed image is transformed into HSV color space representation in order to analyze and establish a color contrast gradient. The multiscale morphological gradient of the intensity channel of the original preprocessed image is obtained and multiplied with the color contrast gradient. The shape feature is extracted based on the descriptors: compactness, convexness, rectangularity and eccentricity, moment invariants. Markers are extracted for this image and given as input to the watershed algorithm which uses a Hill-Climbing approach to identify and label the neighborhood pixels. This algorithm may reduce the computational complexity by avoiding the process of computing lower-complete image.

The proposed system is organized as follows. In section 4, the formation of composite color gradient image based on color contrast gradient and multiscale morphological gradient is explained. Section 5, describes the shape feature extraction based on the descriptors. The texture segmentation algorithm (watershed transform), which applies the hill-climbing approach based on the marker extraction, is analysed in section 6. The experiments and quantitative evaluation are discussed in section 7.

4 Extraction of Composite Color Gradient Image

The proposed texture segmentation algorithm is performed based on the spectral, shape, and intensity features extracted from the preprocessed image. In which the color contrast gradient and multiscale morphological gradient are combined to form the composite color gradient image.

The procedure for constructing Composite Color Gradient Image (CCGI) is given below:

a. Read the Preprocessed Image *PI*. Assign Reference Image *RI* = *PI*
b. Convert *RI* into *HSV* color space.
c. Quantize *H, S, V* values into levels *37, 5, 9* respectively yielding H_q, S_q & V_q values.
d. Find the difference matrices of H_q, S_q & V_q to yield H_d, S_d & V_d related to its eight neighbors.
e. Calculate the Color Contrast Gradient (*CCG*) using Difference & Weight matrices of Value and Hue components.
f. Normalize the gradient values to fall in the range 0 to 10 to yield Normalized Color Contrast Gradient Image (*NCCGI*).

g. Extract the Intensity channel (*I*) of the preprocessed image.
h. Find Multiscale Morphological Gradient Image (*MMGI*) of *I*.
i. Multiply *MMGI* with *NCCGI* to yield Composite Color Gradient Image (*CGI*).
j. Halt

4.1 Preprocessing

A watershed segmentation algorithm can give better output without over-segmentation on a preprocessed noise free image. During image formation an image may be corrupted by very small details (i.e., the sudden discontinuity in gray value over very small regions) which are usually considered as noise. Mostly all segmentation algorithms often need a preprocessing step like noise smoothing to minimize the effects of these undesired perturbations. When morphological operations are used for preprocessing, the noise particles which are less than the scale are well eliminated. In this paper, the algorithm makes use of an Iterative Adaptive Switching Median Filter algorithm which makes possible the perfect removal of impulse noises from images corrupted with higher or lower quantum of impulse noise in the most efficient manner while keeping the fine details of the image intact by leaving the uncorrupted pixels untouched. The resultant image is free from patchy effects and this technique is very effective when images are corrupted with large percentage of impulse noises. Unless the images are preprocessed, the segmentation results may lead to false detection of abnormal cells. To overcome this problem, Morphological Smoothing is applied to yield a preprocessed image.

4.2 Color Contrast Gradient Image

In general, color images are represented in RGB color model. Though RGB is an ideal model for color generation, its usage is limited for color description. Since the three components R, G and B are highly correlated, the chromatic information is not suitable for direct usage. HSV model is an ideal tool for developing image processing algorithms. The three dimensions of color Hue, Saturation and Value constitutes a color model that describes how humans naturally respond to and describe color. The HSV color model is shown in Fig.1.

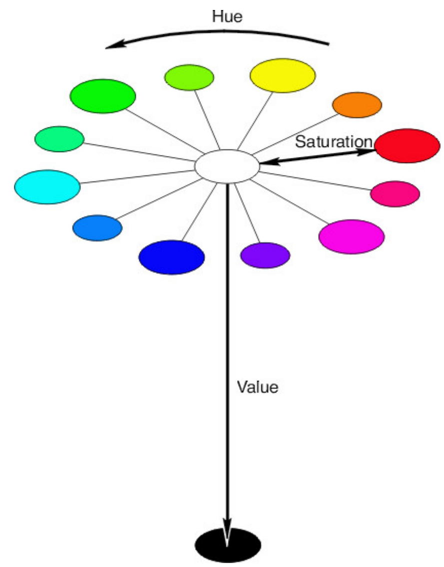

Fig.1. HSV color model

Hue is described by the dominant wavelength in models. Saturation refers to the dominance of hue in the color. It gives a measure of the degree to which a pure color is diluted by white light. When the center of the wheel is reached, no hue dominates. The colors directly on the central axis are considered desaturated. These desaturated colors constitute the gray scale; running from white to black with all the intermediate grays in between. Saturation, therefore, is the dimension running from the outer edge of the hue wheel (fully saturated) to the center (fully desaturated), perpendicular to the value axis. Value constitutes a color model that describes how humans naturally respond to and describe color. If hue can be thought of as a dimension going around a wheel, then value is a linear axis like an axis running through the middle of the wheel.

The conversion of RGB to HSV color model is given below:

$$Max = \max(R, G, B);$$
$$Min = \min(R, G, B);$$
$$Value = Max$$
$$Saturation = \frac{Max - Min}{Max}$$
$$Hue = \begin{cases} \left(\dfrac{G-B}{Max - Min}\right)\Big/6 & if\ \ R = Max \\ \left(2 + \dfrac{B-R}{Max - Min}\right)\Big/6 & if\ \ G = Max \\ \left(4 + \dfrac{R-G}{Max - Min}\right)\Big/6 & if\ \ B = Max \end{cases}$$

The named colors will be in non-uniform quantized position of the Hue plane and it is difficult to measure the distance between any two colors. To reduce this variation and to simplify the image, H, S & V values are uniformly quantized into 37, 5 & 9 levels respectively. The original Hue plane is divided into 37 levels. The Value plane is quantized to 9 levels and Saturation plane into 5 levels. Finally the (H_q, S_q, V_q) represent the quantized values of (H, S, V).

Since the perceptible colors vary with different chromatic conditions, two colors are perceptibly different when the difference of their quantized Hue level is more than three in the highly chromatic situation. In order to emphasize the importance of Hue, the Color Contrast Gradient (CCG) is defined as follows:

$$CCG_{i,j} = MAX((V_d * w_v)(2 * H_d) * w_h) \tag{1}$$

where V_d and H_d are the difference matrices of brightness and hue of the pixel *(i, j)* related to its eight neighbors, w_v & w_h are the related weight matrices depending on the saturation level. Finally the gradients are normalized to be in the range from 0 to 10 to yield Normalized Color Contrast Gradient Image (*NCCGI*).

4.3 Multiscale Morphological Gradient Image

The intensity channel (*I*) of the preprocessed image is extracted and Multiscale Morphological Gradient Image (*MMGI)* is obtained in order to reduce many irrelevant minima and to keep the edges of the objects.

The local gray-level variation in the image can very well be given by the Morphological Gradient. A gradient helps detecting ramp edges and avoids thickening and merging of edges providing edge-enhancements. The Gradient Image, *GI* is morphologically obtained by subtracting the eroded image, *EI* from its dilated version, *DI.*

$$GI = DI - EI \tag{2}$$

A Multiscale Morphological Gradient, *MMGI* is the average of morphological gradients taken for different scales of the Structure Element (SE), B_i.

$$MMGI = \frac{1}{n}\sum_{i=1}^{n}(\partial(MRI, B) - \varepsilon(MRI, B)) \tag{3}$$

where B_i is a SE of size *(2i+1) x (2i+1).*

The noise and quantization errors in the homogeneous regions of the image may produce many insignificant minima in the resulting gradient image which causes over segmentation when subjected to watershed segmentation algorithm. To overcome this drop-out i.e. to eliminate the irrelevant minima, the Multiscale Morphological Gradient Image, *MMGI* is dilated with a SE of smaller size and the local minima with very low contrast can be removed by adding a constant gray value *h,* which is approximately 30 percentile of the histogram of the dilated *MMGI.* A Final Gradient image, *FGI* is obtained by reconstructing the Multiscale Morphological Gradient Image, *MMGI* with its dilated image as a reference image.

$$FGI = \Phi^{rec}\left(\left(MMGI \oplus B\right) + h, MMGI\right) \tag{4}$$

The Normalized Color Contrast Gradient Image (*NCCGI*) is multiplied with the Multiscale Morphological Gradient (*MMGI*) of the intensity image to yield a Composite Color Gradient Image (*CGI*).

5 Shape Feature Extraction

It is important to extract effective features to distinguish regions from one object to other objects. Simple shape analyses can be applied to eliminate obvious false regions. In our algorithm, the following shape descriptors [13] are adopted.

1) *Compactness*. Compactness is given as

$$Compactness = \frac{(Perimeter)^2}{Area} \tag{5}$$

2) *Convexness*. Let *S* represent a set of contour points obtained from level set and *CH*(*S*) be defined as its convex hull. The convexity measure is defined as

$$CM(S) = \frac{Area(S)}{Area(CH(S))} \tag{6}$$

3) *Rectangularity and eccentricity*. The simplest eccentricity is the ratio of the major to the minor axes of an object approximated by its best fit ellipse. Objects are commonly long and thin; therefore, it can be adopted as a shape feature. Rectangularity is the maximum ratio of region area to the area of a bounding rectangle according to its different directions. It assumes values in the interval (0, 1], with 1 representing a perfectly rectangular region.

4) *Moment invariants*. Moments are extensively used for shape representation, pattern recognition, and image

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reconstruction, which make them a very useful feature set to include.

6 Modified Watershed Transform

The Watershed segmentation algorithm applied directly to the Composite Color Gradient Image can cause over-segmentation due to serious noise patches or other image irregularities. So, markers are extracted from the Composite Color Gradient Image using Fuzzy Optimal Threshold value (T_{opt}) obtained for the image *I*.

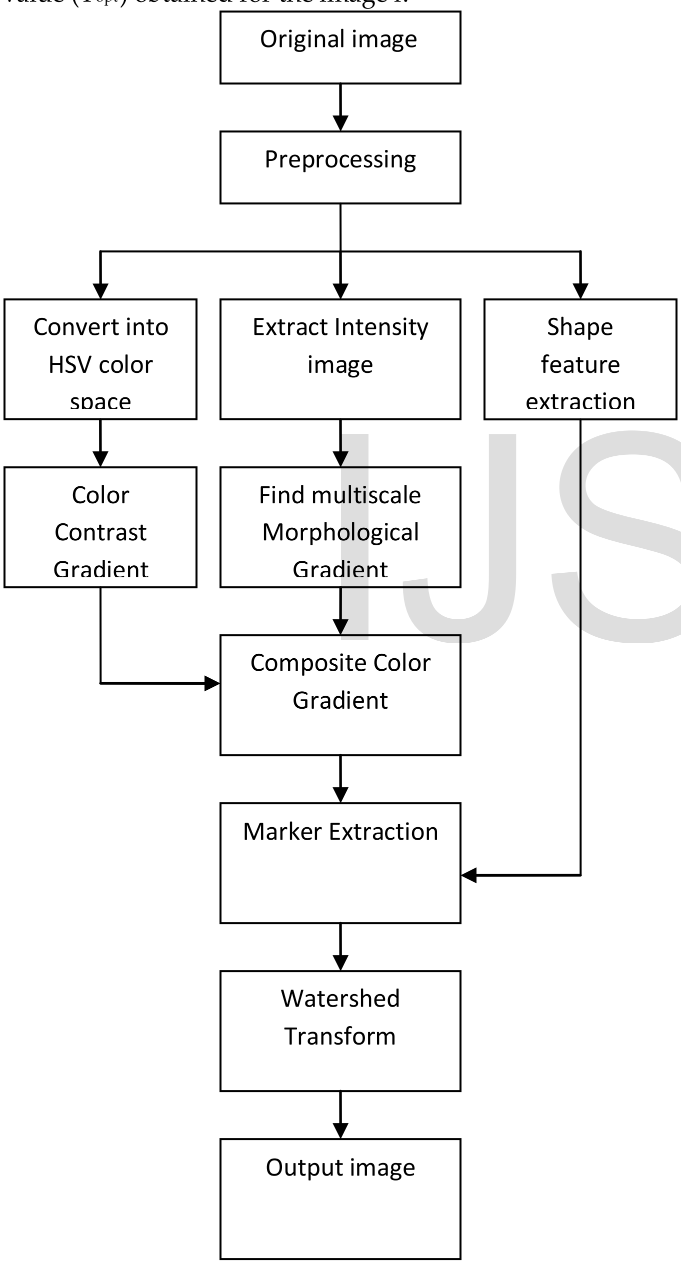


Fig.2. Block Diagram of Proposed System

Fig.2 shows the block diagram of the proposed system. Based on the composite color gradient image, obtained in section IV and the shape feature described in section V, markers are extracted and given as input to the watershed transform, where the image is segmented into different regions.

A watershed segmentation algorithm using Hill-Climbing approach proposed by Moga [14] makes use of parallel architecture which clearly identifies the homogenous regions but the contours of the objects are not well defined. If the image contains mosaic patterns, this approach will not effectively partition or segment the regions. The input gradient image is transformed into a Lower-Complete image. This transformation involves *O (m x n)* multiplications and additions, where m x n is the size of the input image. It yields high computational as well as increasing time complexity. So to address this problem this algorithm introduces a modified Hill-Climbing technique to generate a label image which reduces the computational complexity in two ways. In this algorithm, the process of computing Lower-Complete Image is avoided. The labelling is provided in one scan rather than two scans by the use of two queues. The flooding should progress only between two neighboring pixels whose steepest lower complete neighbour and distance values satisfy the flooding ordering relation. Once a pixel has received a label, it is correctly incorporated in the region it belongs.

For each pixel *P*, if all the neighbours are having higher pixel value, *P* is taken as a regional minimum and labelled. Otherwise the pixel is taken as plateau. Starting from the inner label pixels all the outer pixels with the same gray values are identified. The pseudo-code for the flooding phase of the proposed algorithm is presented below.

Procedure
    Input: Marker Extracted Composite Color gradient image
    Output: Label image L
    Initialize: INIT =-2; NARM=-1; MIN_DIST =0; CURRENT_LABEL=1;
        Initialize the Label image L with INIT;
    For all *p* with *L (p)* EQ INIT Do
        CURR_DISTANCE=1;
        Initialize the queues Qpd and Qpa;
    While queue Qpd is not empty Do
        Dequeue the pixel *q* from the queue Qpd;
    For all *r* EQ *N (q)* {for all neighbors of *q*} Do
      If the gray value of *r* EQ gray value of *q* then
        Assign the CURRENT_LABEL to *L(r)* and Insert the pixel r into Qpd;
      Else if the gray value of *r* LT gray value of *q* then

Assign the CURR_DISTANCE to *L(r)* and enqueue the pixel *q* into the queue Qpa;
End if
End for
End while
Increment the CURR_DISTANCE;
If queue Qpa is empty then
Increment the CURRENT_LABEL;
Else
Find the geodesic distances of the inner pixels of the non-minima plateau and assign the NARM label to non-minima pixels;
End If
End For

The resultant label image is imposed on the original input image to yield the output segmented image.

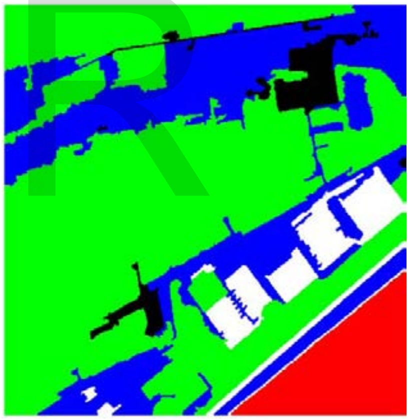
7 Results and Discussions

Fig. 3(a) shows a SPOT5 image of Shanghai, China, with a size of 512 × 512 acquired on September 30, 2005. It includes six land-cover types: residential areas, industrial areas, river, cultivated lands, and culture ponds. The residential areas with spectral features different from others have low homogeneity and high spectral variance. The industrial areas also have high spectral variance with regular strip texture. The river and culture ponds are fine textured with uniform spectral features. The cultivated lands have high spectral variance and low texture differences. Fig. 3(b) shows the segmentation result obtained based on only texture features. Fig. 3(c) shows the final segmentation result of the proposed algorithm obtained based on the spectral, shape, texture, and intensity features.

(a)

The segmentation results are evaluated based on visual interpretation and a quantitative evaluation. For the aspect of subjective visual interpretation, the segments can be divided into two ranks: main and small objects; a segment cannot contain the same rank objects. If segment A belongs to the rank of main object, then it should not contain any other main objects. The main objects are the regions with large areas containing the main content of the image, such as forests, farmland, residential areas, etc. The small objects are small areas, like an isolated house, a special sign, etc. The effects of these two objects on segmentation are different.

(b)



(c)

Fig. 3. Experiment on SPOT5 Image. (a) Original Image (b) Result obtained only by texture segmentation (c) Final texture segmentation result based on spectral, shape and intensity features.

The main objects have the greater impact on the segmentation. As the small and lineal objects always exist in remote sensing images, their interpretations are indispensable. Then, the correctness of shapes and edges of segments is judged through visual interpretation. The main principle is whether edges are smooth or not and whether the shapes are branched or not.

The algorithm discussed in section VI, generate a label image, which reduces the computational complexity. The quantitative evaluation in Table1 shows the evaluation of segmentation results compared with those of existing method. It is performed based on the maximum segmentation accuracy, which can be achieved by the segmentation result. Overall, the proposed algorithm gives a better performance in image segmentation, particularly for regions with regular texture.

TABLE I
QUANTITATIVE COMPARISON OF SEGMENTATION ACCURACY ACHIEVED BY OUR ALGORITHM WITH THAT PROVIDED BY EXISTING ALGORITHM

		Manual Segmentation	Existing Method	Proposed Method
SPOT5 Image	Main Objects	22	15 (68.2%)	16 (72.7%)
	Small Objects	10	8 (80.0%)	8 (80.0%)
	Total	32	23 (71.8%)	24 (75%)

8 CONCLUSION

All the features in images, including spectral, texture, and shape features, are useful for image understanding. However, when they are used to describe the same object, they may give different, even contradictory, results. Combination of the features is a challenging problem.

In this paper, a modified texture segmentation algorithm using spectral, shape and intensity features has been proposed, that avoids over-segmentation and detects better and more exact boundaries between regions. The segmentation is performed based on the markers extracted from the composite color gradient and the shape descriptors. The Hill-Climbing approach reduces the computational complexity by avoiding the process of lower-complete image and the labelling in one scan rather than two scans by the use of two queues. Therefore, the proposed algorithm is aimed to improve the segmentation accuracy between 10% and 20% compared with that of using only purely spectral features.

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