Technical Note

Rough Segmentation of Natural Color Images Using Fuzzy-Based Hierarchical Algorithm

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This paper proposes rough segmentation of natural color images using fuzzy-based hierarchical algorithm. $L^\star a^\star b^\star$ color space is used to represent color features and Statistical Geometrical Features (SGF) are adopted as texture descriptors. Homogeneity decision makes a fusion of texture features and color features with fuzzy-rule theory. Hierarchical segmentation based on the fuzzy homogeneity decision is performed in four processes: hierarchical splitting, local agglomerative merging, global agglomerative merging and pixelwise classification. Experiments on segmentation of natural color images are presented to verify the effectiveness of the proposed approach in obtaining rough segmentation.

1. Introduction

Image segmentation is a process to partition an image into meaningful regions according to some features for subsequent processing. The approaches for segmentation of textured color images can be divided into two categories. One category is to extract color texture features of each color band or across different bands for segmentation [1),2)], and the other is to process gray texture features and color features independently [3),4)]. Both of them face some problems. The disadvantage of the first category is a large feature space, which is not only computational consuming, but will bring about redundant information for segmentation. The difficulty of the second category is how to measure the similarity of different color textures according to both texture features and color features even with contradictory information.

This paper presents rough segmentation of natural color images using fuzzy-based hierarchical algorithm, which belongs to the second category of segmentation. Rough segmentation means that each main object or meaningful part of an object should be represented by one region respectively without paying much attention to region interiors, which is one of the challenging problems in image segmentation [5)]. In order to improve the defect of the second category, it is necessary to adopt an effective segmentation method with a similarity measure making good use of texture features and color features.

We propose a fuzzy-based hierarchical segmentation algorithm that uses fuzzy homogeneity decision for similarity measure of different color textures. We have proposed the modified hierarchical segmentation algorithm of gray textured images [6)] to solve the time consuming problem of the algorithm in the original hierarchical segmentation algorithm [7)]. In this paper, we further expand the modified algorithm to the segmentation of natural color images in combination with fuzzy logic. The hierarchical segmentation is performed in four steps: hierarchical splitting, local agglomerative merging, global agglomerative merging and pixelwise classification. During the whole procedure of hierarchical segmentation, we measure the similarity of any adjacent regions by a fuzzy fusion process which combines the similarity of texture features and color features with different weights of importance. The adoption of fuzzy homogeneity decision simplifies the complex mechanism of integrating different features by using symbolic representations associated with rule-base systems. It also reduces the difficulty of choice of many thresholds inherent in segmentation methods. $L^\star a^\star b^\star$ color space is employed to represent color features [8)]. Statistical Geometrical Features (SGF) [9)] are used as texture descriptors because they can easily discriminate various types of textures. We make some experiments to verify the effectiveness of the proposed method in obtaining rough segmentation of natural color images.

2. Color and Texture Descriptors

2.1 $L^\star a^\star b^\star$ Color Space

$L^\star a^\star b^\star$ color space is a perceptually uniform color space, where $L^\star$ represents intensity, $a^\star$ and $b^\star$ represent chrome information. We obtain $L^\star a^\star b^\star$ color space from RGB color space, then the three components are normalized and

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used as three color features.

2.2 Statistical Geometrical Features

The *SGF* are based on the statistics of geometrical properties of connected regions in a sequence of binary images obtained from a textured image, which is the $L^\star$ component intensity image of a color image. The extraction starts by thresholding the image into a number of binary planes. Then the number of connected 1-valued and 0-valued regions in each plane gives two geometrical and two irregularity measures. Each of these four functions are further characterized by the maximum value, the average value, the sample mean and the sample standard deviation. After the *SGF* for each plane are obtained, 16 feature measures for a textured image can be obtained. A sliding overlapping window of size 5×5 is used for calculating the *SGF* of each pixel of a textured image.

3. Fuzzy-Based Homogeneity Decision

Homogeneity decision is a measure to test similarity of regions under consideration during segmentation procedure. For any two regions, we first set fuzzy rules for homogeneity measures of *SGF* texture features and $L^\star a^\star b^\star$ color features of them, respectively, we then obtain a final homogeneity decision by fusing the similarity from the homogeneity measures.

The homogeneity measure principles can be expressed in a plain linguistic statements using if-then rules.

Rule1: if *SGF* difference is SMALL, then HOMOGENEOUSE (HO); else NOT HOMOGENEOUSE (NHO).

Rule2: if $L^\star a^\star b^\star$ difference is SMALL, then PROBABLY HOMOGENEOUSE (PHO); else PROBABLY NOT HOMOGENEOUSE (PNHO).

SGF difference is the Euclidean distance of the 16 *SGF* components between the two regions, and $L^\star a^\star b^\star$ difference is the Euclidean distance of the three $L^\star a^\star b^\star$ components between them. Four homogeneity measures HO, NHO, PHO and $PNHO$ represent different grades of homogeneity of the two regions as shown in **Fig. 1**, and their homogeneity values μ_{HO}, μ_{NHO}, μ_{PHO} and μ_{PNHO} can be obtained from fuzzy membership functions of *SGF* difference and $L^\star a^\star b^\star$ difference as shown in **Fig. 2**. Here ΔS represents *SGF* difference and ΔL represents $L^\star a^\star b^\star$ difference. The limit values of ΔS_{small}, ΔL_{small}, ΔS_{large} and ΔL_{large} are tuned with human expertise.

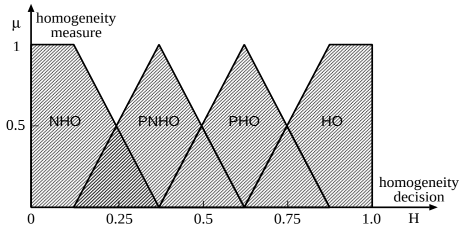


Fig. 1 The fuzzy set used for homogeneity inference.

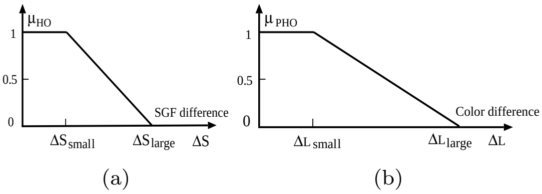


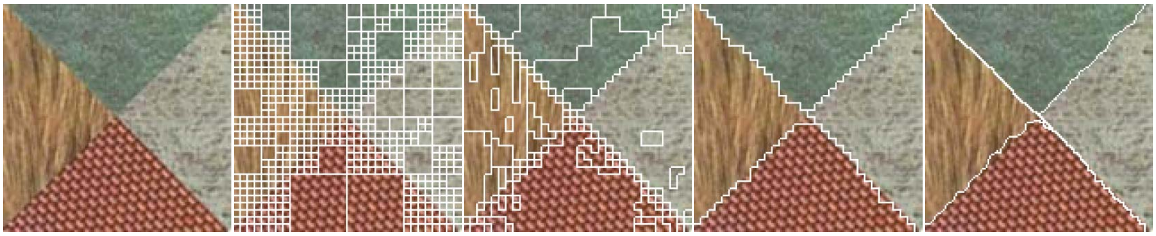
Fig. 2 Fuzzy membership functions of (a) *SGF* difference (ΔS) and (b) $L^\star a^\star b^\star$ difference (ΔL).

Final homogeneity decision H is inferred from the homogeneity measures with a centriod defuzzification method [10]. Suppose the homogeneity limit is set 0.5, then if the inferred homogeneity decision is over 0.5, the regions being concerned are regarded as homogeneous, else not. The fuzzy-rules give the *SGF* a higher priority than the color features because we think the texture features offer more important information for textured color images. Actually, the priority of texture features and color features can be regulated according to the needs.

4. Segmentation Algorithm

The hierarchical segmentation performs in four stages, hierarchical splitting, local agglomerative merging, global agglomerative merging and pixelwise classification. During the whole procedure, fuzzy homogeneity decision H is used as similarity measure. In the following, we will demonstrate the progress of segmentation on a 128×128 color texture mosaic containing four different textures as shown in **Fig. 3** (a).

In hierarchical splitting, the image is first divided into rectangular blocks of size S_{max}. Then the uniformity of these four subblocks based on the analysis of H is tested. We measure six pairwise H between the four subblocks, and get the largest homogeneity decision H_{max} and the smallest H_{min}. If the ratio of H_{max} and H_{min} is lower than a threshold X, and H_{min} is higher than a threshold value Y, then the block is regarded as uniform, otherwise it is split into four subblocks. The process is



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

Fig. 3 Segmentation of a color texture mosaic: (a) original image; (b) result of hierarchical splitting; (c) result of local agglomerative merging; (d) result of global agglomerative merging; (e) result of pixelwise classification.

performed to all the subblocks until the minimum block size S_{min} is reached. The result is shown in Fig. 3 (b). Here $S_{max} = 64$, $S_{min} = 4$, $X = 1.2$ and $Y = 0.5$.

Local agglomerative merging is a process newly proposed by us[6] to combine adjacent segments and to produce larger regions locally. The homogeneity decision between any current segment and its neighboring adjacent regions labeled as a different segment is tested individually. Then the two adjacent segments having the largest homogeneity decision H_{max} are regarded as similar and merged to become one segment if the value of H_{max} is higher than a threshold Z. The process is continued until all segments are scanned. The result at $Z = 0.5$ is shown in Fig. 3 (c).

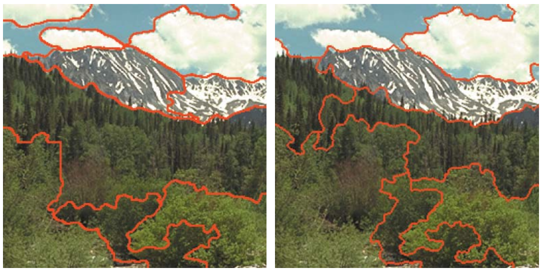
Global agglomerative merging is a process to merge similar adjacent regions globally. Two adjacent segments with the smallest merger importance value among all possible mergers will be merged for each merge. The procedure finds the best possible pair of adjacent segments whose merging will introduce the smallest change in the segmented image until a stopping criterion, the ratio of the merger importance for the current best merger and the largest merger importance of all preceding mergers, exceeds a threshold M. We set $M = 4$ to obtain rough segmentation shown in Fig. 3 (d).

Pixelswise classification is finally performed to improve the localization of boundaries. If an image pixel is on the boundary of at least two distinct textures, a discrete disc will be placed on it. Then the homogeneity decision H between the disc and its neighboring regions is calculated individually to decide if the pixel needs to be relabeled. The next scan will check the neighborhoods of the relabeled pixels until no pixels are relabeled. The final segmentation is shown in Fig. 3 (e). The proposed approach well divides the color texture mosaic into four homogeneous regions.

5. Experimental Results

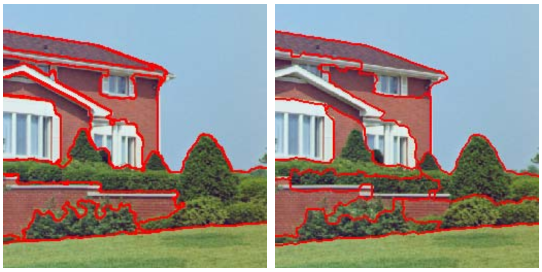
In this section, we conducted experiments in addition to that in Fig. 3 to assess the performance of the proposed segmentation approach. We aim to obtain rough segmentation that is necessary to possess these properties that segmented regions should be uniform, region interiors should not contain a large number of small holes and boundaries of each region should be spatially accurate. We set $S_{max} = 64$, $S_{min} = 4$, $X = 1.2$, $Y = 0.5$, $Z = 0.5$, and M is set differently according to different images to obtain rough segmentation.

We first apply the approach to a 256×256 natural color image shown in **Fig. 4**. The image is composed of blue sky, white clouds, a mountain and forests. The mountain is composed of the right portion heavily covered with snow and the left portion lightly covered with snow, and the color of the forests is different that causes layer effects. Figure 4 (a) is the segmentation result of the proposed algorithm when $M = 1.4$. The result shows rough segmentation in which the sky, the clouds and the two portions of the mountain are all well maintained as complete regions. Though the forests are divided into several parts, the segmentation result corresponds well with the human visual system. Figure 4 (b) is the segmentation result of the EdgeFlow method[5], which is not satisfactory in that some clouds are regarded as the same region as the sky. We chose the best result of the EdgeFlow method from many results with different parameters. The comparison proves the effectiveness of the proposed method.



(a) (b)

Fig. 4 Segmentation of a natural color image: (a) result of the proposed method; (b) result of EdgeFlow method.



(a) (b)

Fig. 5 Segmentation of a natural color image containing man-made objects: (a) result of the proposed method; (b) result of EdgeFlow method.

We then apply the approach to segmentation of a 256×256 natural color image containing man-made objects shown in **Fig. 5**. The image is composed of the sky, a house, trees and a lawn. The boundaries within the house further divide it into the main parts of objects such as roofs, windows and walls. The segmentation is more difficult because it is necessary to obtain accurate boundaries as well as uniform texture regions. The segmentation result of the proposed algorithm at $M = 1.6$ and the EdgeFlow technique is shown in Fig. 5 (a) and Fig. 5 (b), respectively. The proposed algorithm represents a better rough segmentation result than the EdgeFlow method, in which the trees, the lawn and the main parts of the house are well maintained as complete regions, the segmented regions are uniform and the boundaries of each region are maintained spatially accurate, though the time cost of the EdgeFlow algorithm is about half of that of the proposed algorithm on average. Further investigations are necessary to precisely compare the proposed method with other methods.

6. Conclusions

In this paper, we have presented rough segmentation of natural color images using the proposed fuzzy-based hierarchical algorithm. The fuzzy homogeneity decision makes a reliable fusion of texture features and color features. The hierarchical segmentation based on the fuzzy homogeneity decision is effective in obtaining rough segmentation that maintains uniform texture regions and accurate boundaries. The experiments have demonstrated that the proposed method provides promising results for unsupervised rough segmentation of natural color images.

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