NUMBER-DRIVEN PERCEPTUAL SEGMENTATION OF NATURAL COLOR IMAGES FOR EASY DECISION OF OPTIMAL RESULT

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ABSTRACT

This paper proposes number-driven perceptual segmentation of natural color images using a fuzzy-based hierarchical algorithm for an easy decision of the optimal segmentation result. A fuzzy-based homogeneity measure makes a fusion of the $L^{\star}a^{\star}b^{\star}$ color features and the SGF texture features. Proposed hierarchical segmentation method is performed in four stages: simple splitting, local merging, global merging and boundary refinement. The effectiveness of the proposed method is confirmed through computer simulations that demonstrate an easy determination of the optimal segmentation result.

Index Terms— Perceptual image segmentation, natural color images, hierarchical algorithm, fuzzy inference.

1. INTRODUCTION

Image segmentation is a process to partition an image into meaningful regions and is an important step before an image recognition process. In this paper, we are concerned with perceptual segmentation that is defined to obtain segmentation that produces a small number of segmented regions, and each region should represent a main object or a meaningful part of an object without paying much attention to region interiors. For example, a tree that has many branches and leaves is regarded as one object in perceptual segmentation in contrast to the conventional detailed segmentation.

Though there is an extensive literature on image segmentation [1]-[4], the papers on perceptual segmentation are limited. Among them, Mirmehdi and Petrou [5] proposed the method based on the multiscale perceptual tower and the probabilistic relaxation method. Shi and Malik [6] proposed the perceptual grouping method based on graph theory, and Ma and Manjunath [7] proposed the technique based on the Gabor filters and the EdgeFlow. Recently, Chen *et al.* [8] proposed the approach based on the adaptive clustering algorithm and the steerable filter decomposition. Although these methods perform well, their algorithms are complicated and it is not easy to get the optimal segmentation result.

Ideally, the segmentation process should be stopped automatically without human decision. However, there is yet no automatic way of evaluation in perceptual segmentation, and therefore users have to make a substantial effort of tuning the several parameters to acquire the best result. For this reason, it is required to develop a segmentation algorithm that enables users to determine the optimal result more easily.

In this paper we propose a novel technique, a fuzzy-based hierarchical algorithm for perceptual segmentation of natural color images, that is capable of deciding the optimal segmentation result driven by the number of segmented regions. Since the proposed algorithm has the significant advantage to produce the segmentation results by reducing the number of segmented regions one by one at each step, the user is able to determine the optimal result easily just by observing the several segmented results.

In the present work, the expected number of segmented regions is very small and we consider around 5-15 as the optimum range of the number of segmented regions in the sense of perceptual segmentation. In the practical implementation of the proposed algorithm, it is not necessary to observe all the segmented results with 5-15 regions, and the user can decide the best result with an appropriate roughness from among 4-5 segmented results depending on the contents of each image and user's intention.

The proposed algorithm is based on the method of Ojala and Pietik$\ddot{a}$inen [9], and we drastically improved their algorithm in developing number-driven perceptual segmentation of natural color images. The proposed method is a simple algorithm with an easy implementation that has four hierarchical stages: simple splitting, local merging, global merging and boundary refinement. During the latter three stages, we measure the similarity of any adjacent regions using fuzzy homogeneity [10] that combines the similarity of color features and texture features with different degrees of importance. We use the $L^{\star}a^{\star}b^{\star}$ color space to represent color features and the Statistical Geometrical Features (SGF) [11] as texture features. The adoption of a fuzzy-based homogeneity measure simplifies the complex mechanism of integrating different features by means of symbolic representations. It also reduces the difficulty in choosing the parameters inherent in segmentation methods, though the tuning of the fuzzy membership functions is still required for each image. Several experiments are made to confirm the effectiveness of the proposed method in comparison with another method.

2. COLOR AND TEXTURE FEATURES

2.1. $L^{\star}a^{\star}b^{\star}$ Color Features

The $L^{\star}a^{\star}b^{\star}$ color space is a perceptually uniform color space, in which $L^{\star}$ represents brightness and $a^{\star}$ and $b^{\star}$ represent chromatic information. We obtain the $L^{\star}a^{\star}b^{\star}$ color space from the RGB color space, and then the three components, $L^{\star}$, $a^{\star}$ and $b^{\star}$, are normalized and used as three color features.

2.2. SGF Texture Features

The SGF [11] are a set of texture features based on the statistics of geometrical properties of connected regions in a sequence of binary images obtained from an original image. The extraction of the SGF starts by thresholding each component ($L^{\star}$, $a^{\star}$ and $b^{\star}$) of a color image with a threshold value α that produces numbers of binary images.

Each binary image comprises several connected regions. The number of connected regions of 1-valued pixels and that of 0-valued pixels give two geometrical measures, $NOC_1(\alpha)$ and $NOC_0(\alpha)$, respectively. Next a measure of irregularity (or a measure of non-circularity) is defined to each of the connected regions. The average of irregularity measure of 1-valued pixels in the binary image and that of 0-valued pixels are represented as $\overline{IRGL_1}(\alpha)$ and $\overline{IRGL_0}(\alpha)$, respectively.

Each of these four functions is further characterized using the three statistics over an entire image: the average value, the sample mean and the sample standard deviation. This gives a total of 36 texture features. A sliding overlapping window of size 5×5 is used to calculate the SGF of each pixel of an original image.

3. FUZZY-BASED HOMOGENEITY MEASURE

Homogeneity is a measure to test the similarity of two regions under consideration during the segmentation procedure. We adopt a fuzzy-based homogeneity measure to integrate the different features: the $L^{\star}a^{\star}b^{\star}$ color features and the SGF texture features. We use the following fuzzy rules in which each rule has a corresponding membership function.

1) Rule 1: *If* SGF difference is SMALL, *Then* HOMOGENEOUSE (HO); *Else* NOT_ HOMOGENEOUSE (NHO).

2) Rule 2: *If* $L^{\star}a^{\star}b^{\star}$ difference is SMALL, *Then* PROBABLY_ HOMOGENEOUSE (PHO); *Else* PROBABLY_ NOT_ HOMOGENEOUSE (PNHO).

These fuzzy rules give the SGF texture features a higher priority than the $L^{\star}a^{\star}b^{\star}$ color features because we consider that the texture features provide more important information in perceptual segmentation of textured color images. In these fuzzy rules, a SGF difference is the Euclidean distance of 36 SGF between two regions under consideration, and a $L^{\star}a^{\star}b^{\star}$ difference is the Euclidean distance of three color components between them.

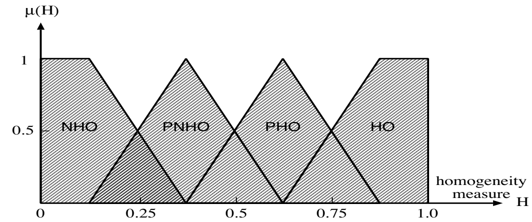

Fig. 1. The fuzzy sets used for homogeneity inference.

Four conditions HO, NHO, PHO and $PNHO$ represent different grades of homogeneity between two regions. After fuzzification by applying the above two rules, min-max inference takes place using the fuzzy sets shown in Fig. 1. Then the conventional centroid defuzzification method is applied. Suppose the homogeneity limit is set to be 0.5. Then, if the inferred homogeneity measure is over 0.5, the two regions being concerned are regarded as homogeneous and they are merged. We use the value of the homogeneity measure H in the proposed segmentation algorithm.

4. SEGMENTATION ALGORITHM

In the proposed segmentation procedure, we first obtain the $L^{\star}a^{\star}b^{\star}$ color features and the SGF texture features for each pixel of an original image. We then execute the segmentation algorithm in four stages: simple splitting, local merging, global merging and boundary refinement. During the latter three stages, the fuzzy-based homogeneity measure H is used as a similarity measure. In the following, we will demonstrate the progress of the proposed segmentation algorithm for a 300×300 natural color image shown in Fig. $2(a)$.

4.1. Simple Splitting

In simple splitting, an original image is divided into rectangular subblocks of size 4×4 as shown in Fig. $2(b)$.

4.2. Local Merging

Local merging is a newly proposed stage by us to merge adjacent regions locally for drastically reducing the number of regions to be used at the stage of global merging. The SGF of each 4×4 subblock are obtained by averaging the texture features of all pixels within the subblock, so does the $L^{\star}a^{\star}b^{\star}$ color features of each subblock.

The homogeneity between any current region and its neighboring adjacent region is measured individually. Then the two adjacent regions having the largest homogeneity measure H_{max} are regarded as similar and they are merged to become one region if the value of H_{max} is higher than a threshold 0.5. The process is continued until all regions are scanned. The result of local merging is shown in Fig. $2(c)$.

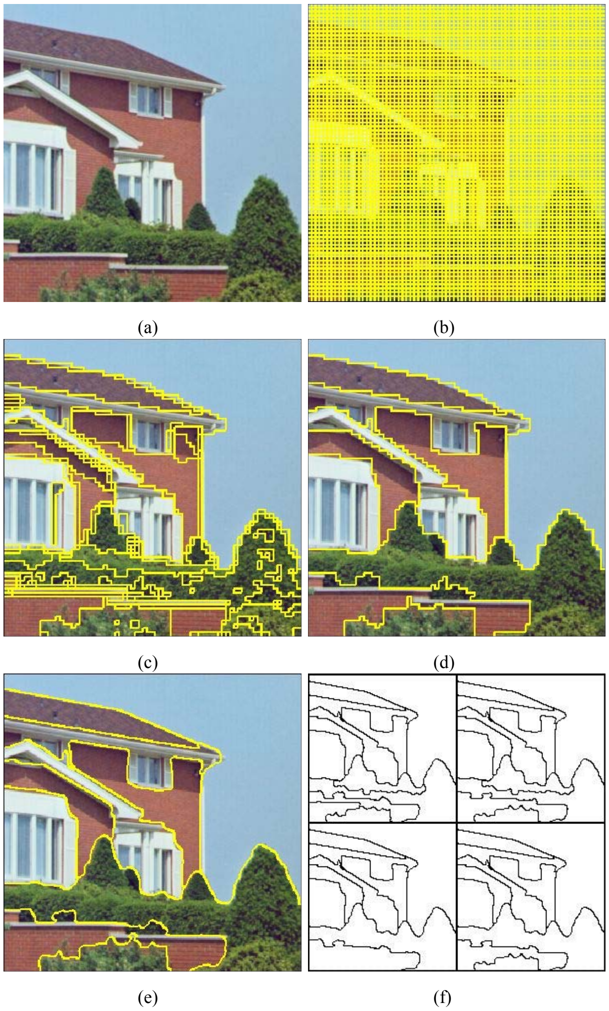

Fig. 2. Progress of the proposed segmentation algorithm: (a) original image; (b) result of simple splitting; (c) result of local merging; (d) result of global merging with $N = 10$; (e) result of boundary refinement; (f) results of segmentation with $N = 12$, 11, 10 and 9 shown clockwise from the upper left.

4.3. Global Merging

Global merging is a stage to merge similar adjacent regions globally. A pair of adjacent regions with the smallest merger importance value among all possible mergers in an entire image will be merged at each step. Merger importance MI is defined as the ratio of the number of pixels in the smaller region to the homogeneity measure of adjacent regions

$$MI = \frac{P_{small}}{H}. \tag{1}$$

This procedure finds the best possible pair of adjacent regions globally whose merging introduces the smallest change in the segmented image. Since global merging reduces the number of segmented regions one by one at each step and merger importance removes the less important regions first, the essential regions remain to the end and thus perceptual segmentation is achieved. It is also easy to stop the algorithm at the specified number of segmented regions N. Fig. $2(d)$ shows the result of global merging when we set $N = 10$.

4.4. Boundary Refinement

Boundary refinement is finally performed to improve the localization of boundaries. If an image pixel is on the boundary of at least two distinct regions, a discrete disk with radius 3 will be placed on it. Then the homogeneity measure H between the disk and its neighboring region 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 result of boundary refinement is shown in Fig. $2(e)$.

In the practical implementation, we can easily choose the desirable optimal result with an appropriate roughness by observing the several segmented results. The results of segmentation when we set $N = 12, 11, 10$ and 9 are shown clockwise from the upper left in Fig. $2(f)$. This figure demonstrates how the number of segmented regions decreases in the proposed algorithm.

5. EXPERIMENTAL RESULTS

We present the experimental results to assess the performance of the proposed segmentation method. For comparison, we show the results of the EdgeFlow method using the algorithm made by the authors [12]. Since the EdgeFlow algorithm cannot produce the specified number of segmented regions, we chose the best result with the nearest number of segmented regions to our result by tuning the parameters. In our algorithm, we have to tune two parameters of the fuzzy membership functions differently according to each image and they were determined empirically.

We applied the proposed method to 300×300 natural color images containing man-made objects shown in Fig. $3(a)$ and (e). The perceptual segmentation is rather difficult because it is necessary to obtain accurate boundaries as well as uniform texture regions. Fig. $3(b)$ and (f) show the results of perceptual segmentation using the proposed algorithm when we set $N = 14$, 13, 12 and 11 and $N = 9$, 8, 7 and 6, respectively. The user can easily decide the optimal result by observing these segmented results. The selected optimal results with $N = 12$ and $N = 7$ are shown in Fig. $3(c)$ and (g), respectively. The results of segmentation using the EdgeFlow method are shown in Fig. $3(d)$ and (h). Although two algorithms provide the same degree of rough segmentation, the proposed algorithm clearly shows better results than the EdgeFlow method, namely, the segmented regions are more uniform and the boundaries of each region are maintained spatially more accurate.

These comparisons demonstrate the effectiveness of the proposed method. However, further investigations are necessary to precisely compare the proposed algorithm with other methods.

6. CONCLUSIONS

In this paper, we presented perceptual segmentation of natural color images using the proposed fuzzy-based hierarchical algorithm. Since the fuzzy-based homogeneity measure makes a reliable fusion of the $L^{\star}a^{\star}b^{\star}$ color features and the SGF texture features, the proposed method provides perceptual segmentation that maintains uniform texture regions and accurate boundaries. The proposed algorithm also has the significant advantage of easily deciding the optimal segmentation result with an appropriate roughness by observing the several segmented results.

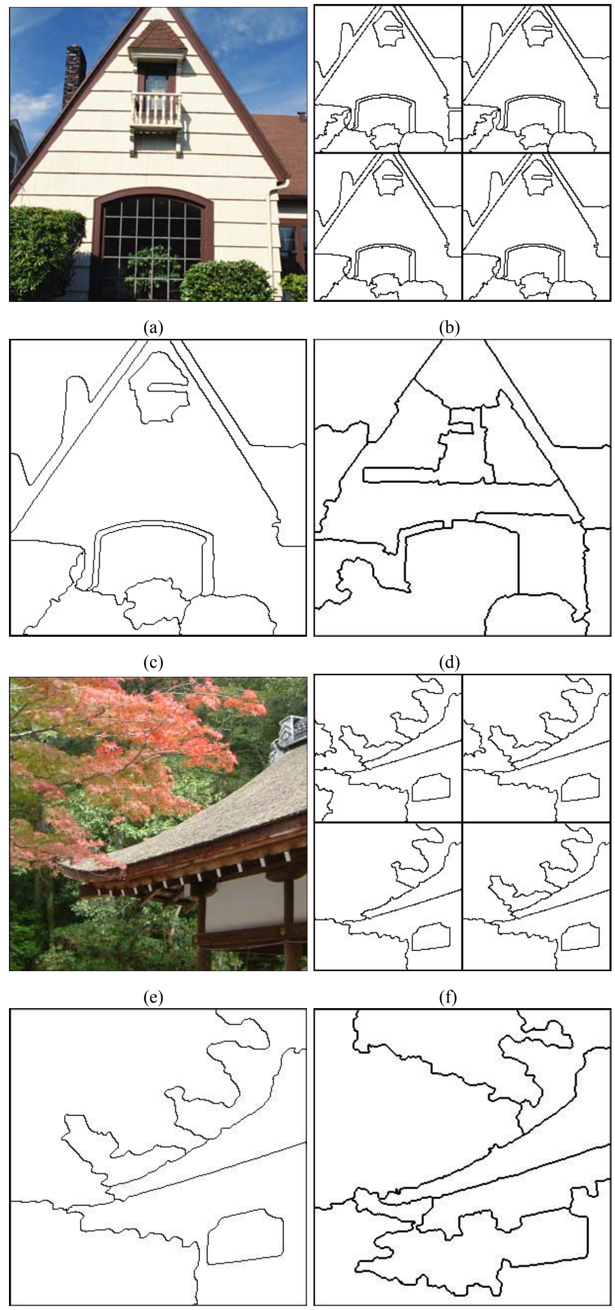

Fig. 3. Segmentation of natural color images containing man-made objects: (a) original image; (b) results of proposed method with $N = 14$, 13, 12 and 11 shown clockwise from the upper left; (c) result of proposed method with $N = 12$; (d) result of EdgeFlow method; (e) original image; (f) results of proposed method with $N = 9$, 8, 7 and 6 shown clockwise from the upper left; (g) result of proposed method with $N = 7$; (h) result of EdgeFlow method.

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