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Segmentation of Natural Images Using Fuzzy Region-Growing Algorithm

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We present a new method that integrates intensity features and a local fractal-dimension feature into a region growing algorithm for the segmentation of natural images. A fuzzy rule is used to integrate different types of features into a segmentation algorithm. In the proposed algorithm, intensity features are used to produce an accurate segmentation, while the fractal-dimension feature is used to yield a rough segmentation in a natural image. The effective combination of the different features provides the segmented results similar to the ones by a human visual system. Experimental results demonstrates the capabilities of the proposed method to execute the segmentation of natural images using the fuzzy region-growing algorithm.

Keywords: Image Segmentation, Region-Growing Algorithm, Fuzzy Rules, Local Fractal Dimension, Natural Images

1 INTRODUCTION

The purpose of this paper is to segment natural images with different precision. For a natural image containing houses and trees, we execute an accurate segmentation for a part of the houses and a rough segmentation for a part of the trees. We would like to regard the part of trees including many branches and leaves as the same region as much as possible, while keeping high-precise segmentation at the part of the houses.

It is known that the fractal dimension (FD) of the image is a powerful measure for natural images, since it has been shown that the FD has a strong correlation with human judgement of surface roughness(1). Although several results of segmentation based on the FD have been reported, the FD alone does not perform a good segmentation because of the low resolution of the FD in natural images(2),(3).

Proposed in this paper is a new segmentation algorithm that integrates intensity features and a FD feature into a fuzzy region-growing algorithm in segmenting natural images. In the proposed method, the intensity features are used to produce an accurate segmentation at the part of non-texture regions such as the houses, while the FD feature is used to yield a rough segmentation at the part of texture regions such as the trees. The low resolution of the FD becomes advantageous in performing a rough segmentation. In this paper we use a blanket method to estimate the local FD(4),(5),(6). Furthermore, we have estimated an optimum number of the blanket suitable for the local estimation of the FD. We have used a fuzzy set theory in order to integrate different types of features into a region growing algorithm(7),(8).

The paper is organized as follows. The second section provides the background on estimating the FD and discusses an optimal estimation of the local FD. Section 3 introduces new fuzzy rules to integrate the different features based on the region growing algorithm. In section 4, we present some results of computer simulations that demonstrate the capabilities of the proposed segmentation algorithm in segmenting natural images. Finally, conclusions are made.

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2 ESTIMATION OF LOCAL FRACTAL DIMENSION

In the blanket method, an upper and lower blanket are grown from the image surface[4]. If ε is the number of the blanket, and u_ε and b_ε are the upper and lower blanket surfaces at position (i, j), then the surface area of the blanket is calculated as follows:

$$A(\varepsilon) = \frac{\sum\sum (u_\varepsilon(i,j) - b_\varepsilon(i,j))}{2\varepsilon} \quad \cdots\cdots\cdots (1)$$

On the other hand, the area of a fractal surface behaves like[9]

$$A(\varepsilon) = F\varepsilon^{2-D} \quad \cdots\cdots\cdots (2)$$

where F is a constant and D is the FD of the image. Therefore, the FD can be estimated from the slope of the straight line if $A(\varepsilon)$ versus ε is plotted on a log-log scale. However, the actual plot is not a straight line but a nonlinear curve especially for the small local area or window. Therefore, the value of the estimated FD will change according to the maximum number of the blanket to be used in the estimation. Since it is desirable to use the local area as small as possible for the purpose of image segmentation, it is necessary to decide the optimum number of the blanket for a small window.

We have evaluated the behavior of the local FD when we change the number of the blanket in calculating the FD for several sizes of window. We have used the window of the following sizes: 3×3, 5×5, 7×7, and 9×9. For a certain size of a window, we estimate each local FD for a fixed number of the blanket by calculating the average of 200 samples taken from a texture image. We have evaluated the sum of the difference (SOD) between the global FD (GFD) and the local FD (LFD) for the several sizes of the window as a function of ϵ:

$$SOD(\epsilon) = \sum_{i=1}^{4} |GFD(\epsilon) - LFD_i(\epsilon)| \quad \cdots\cdots (3)$$

where i corresponds to the four sizes of the window and global FD means the use of 256×256 window. Figure 1 shows the examples of the estimated LFD and GFD for a certain texuture image that demonstrate the variation of the estimated value of FD for four sizes of local windows when we change the maximum number of the blanket (ϵ). Figure 2 represents the minimum values of the sum of the difference (SOD) between the global FD and the local FD when we change the maximum number of the blanket for 40 kinds of texture images from Brodatz album[10]. This figure shows that the number of the blanket between 30 and 58 demonstrates a minimum variation from the global FD in estimating the local FD. Thus we use 44 as the optimum number of the blanket to calculate the local FD in our algorithm.

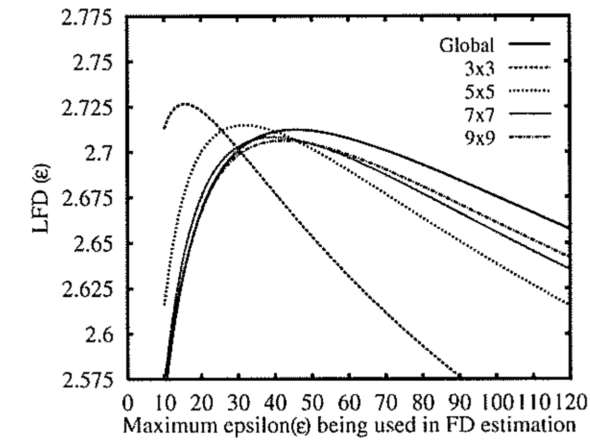

Fig. 1. The sum of the difference between the global and local fractal dimensions.

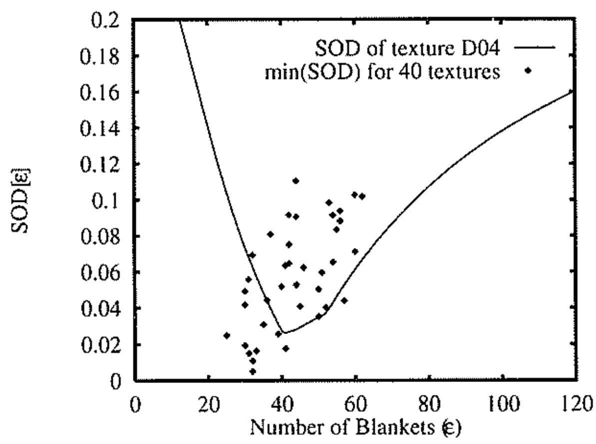

Fig. 2. The sum of the difference between the global and local fractal dimensions.

3 FUZZY REGION-GROWING ALGORITHM

The segmentation procedure in the present investigation is the fuzzy region-growing algorithm that is based on a fuzzy rule. Our final objective is to split an original image I into a number of homogeneous but disjoint regions R_j:

$$I = \bigcup_{j=1}^{n} R_j, \quad R_j \cap R_k = \emptyset \quad j \neq k \quad \cdots\cdots (4)$$

The region growing is essentially a grouping procedure that groups pixels or subregions into larger regions in which the homogeneity criterion holds. Starting from a single pixel, a segmented region is created by merging the neighboring pixels or the adjacent regions around a current pixel. The operations are repeatedly performed until there is no pixel that does not belong to a certain region.

Since our strategy in segmenting natural images is an effective combination of an accurate segmentation by the intensity features and a rough segmentation by the FD feature, it is inevitable to employ a technique of information integration. We adopt fuzzy rules to integrate the different features. We use the following criteria where each fuzzy rule has a corresponding membership function. The intensity features are the intensity difference and the intensity gradient.

In the proposed fuzzy rules, we set a stronger merging rule for the fuzzy set from the FD feature than the one from the intensity features in order to achieve a rough segmentation, that is to create a large region, at the part of the trees. Since the local FD provides broad edges around the true strong edges, however, we employ the boundary edge[(5),(11)] as the intensity gradient to protect the unnecessary growth of regions around the true edges at the part of the houses.

[Rule 1] The first intensity feature is the difference between the average intensity value $g_{ave}(R_k)$ of a region R_k and the intensity value of a pixel $g(i,j)$ under investigation:

$$\text{DIFFERENCE} = |g_{ave}(R_k) - g(i,j)| \ldots. \quad (5)$$

The corresponding fuzzy rule for fuzzy set SMALL is

R1: IF DIFFERENCE IS SMALL THEN PROBABLY MERGE (PM) ELSE PROBABLY NOT_MERGE (PNM).

[Rule 2] The edge information in the region growing algorithm plays an important role. A new pixel may be merged into a region if the gradient between the pixel and the adjacent neighboring region is low. If the gradient is high, the pixel will not be merged. The second intensity feature is the GRADIENT, or the value of boundary edge between the pixel and its adjacent region. We employ the boundary Sobel operator[(5)] to calculate the gradient and to achieve an accurate segmentation at the part of the houses. The fuzzy rule for fuzzy set LOW becomes

R2: IF GRADIENT IS LOW THEN PROBABLY MERGE (PM) ELSE PROBABLY NOT_MERGE (PNM).

[Rule 3] We incorporate the FD feature that is similar to DIFFERENCE in Rule 1. The difference here is taken between tthe average LFD value $D_{ave}(R_k)$ of a region R_k and the LFD value $D(i,j)$ of a pixel under investigation:

$$\text{DIMENSION} = |D_{ave}(R_k) - D(i,j)| \ldots \quad (6)$$

The corresponding fuzzy rule for fuzzy set SMALL2 is the following one that is a stronger merging rule than Rule1 and Rule2, because the role of the FD feature should be emphasized in the proposed algorithm.

R3: IF DIMENSION IS SMALL THEN MERGE (M) ELSE NOT_MERGE (NM).

[Rule 4] The smaller regions, especially regions that consist of one or two pixels, have to be avoided in the region growing algorithm, since it is preferable to remain few large regions instead of many small regions. Thus a fourth rule is the fuzzy set TINY that has the following simple rule:

R4: IF SIZE IS TINY THEN MERGE (M).

Figure 3 shows the four membership functions corresponding to each fuzzy rule. After the fuzzification by the above four rules, min-max inference takes place using the fuzzy sets shown in Fig. 4. Then the conventional centroid defuzzification method is applied. A pixel is really merged when the homogeneity criterion is satisfied to an extent of 50 % after defuzzification.

The final procedure is the merging of two regions that is not a fuzzy rule but a crisp rule after the grouping procedure by the fuzzy inference. Two regions R_j and R_k are recursively merged if

$$|g_{ave}(R_j) - g_{ave}(R_k)| \leq T \ldots\ldots\ldots\ldots\ldots \quad (7)$$

is satisfied, where T is a predetermined threshold.

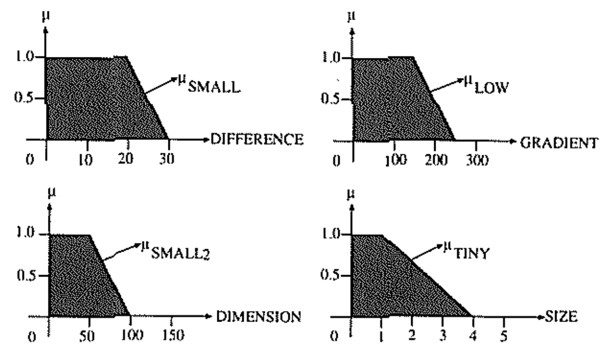

Fig. 3. The membership functions for four fuzzy rules.

4 EXPERIMENTAL RESULTS AND DISCUSSION

To assess the performance of the proposed segmentation method, we have executed the simulated experiments using natural images. We have decided the values of the parameters in the segmentation algorithm empirically, and segmented results are represented by the boundaries

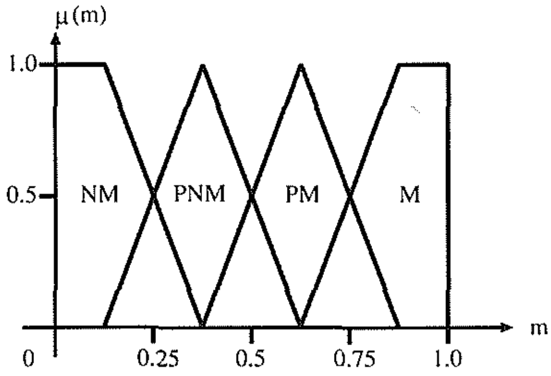

Fig. 4. The fuzzy sets used for inference.

of segmented regions. Figure 5(a) is an original natural image that has 400×400 pixels and 256 gray levels and contains a part of a house and a part of trees. The estimated local FD map by using the blanket method with 3×3 window and 44 blankets is shown in Fig. 5(b) (this image is shown after the linear transformation from 2.0~3.0 to 0~255). The estimated FD demonstrates nearly the same value at the part of the trees that is well suited for a rough segmentation in the proposed method.

We have performed the conventional segmentation method that uses only the intensity features and the proposed method that uses both the intensity and the fractal features. The conventional method is a region growing algorithm that uses the grouping procedure based on a crisp rule. The segmented images by the conventional algorithm and by the proposed algorithm are shown in Fig. 5(c) and 5(d), respectively. The result in Fig. 5(d) faithfully reflects the low accuracy of the local FD and provides a rough segmentation at the part of the trees while keeping an accurate segmentation at the part of the house. The portions of the trees in Fig. 5(d) are roughly regarded as the same region in comparison with the result in Fig. 5(c) in which the part of the tree yields a large number of small regions. The result by the proposed method coincides with one of the functions of the human visual system that considers a few trees including lots of branches and leaves as one region. The numbers of segmented region of the resultant images in Fig. 5(c) and 5(d) are 4478 and 101, respectively. The substantial reduction in the number of regions, together with the appearance of the segmented images, clearly indicates the effectiveness of the proposed algorithm in segmenting natural images.

The results of the second experiment are shown in Fig. 6. Figure 6(a) is the second natural image and 6(b) is the estimated local FD. The segmented results by the conventional algorithm and by the proposed algorithm are shown in Fig. 6(c) (no. of regions: 2586) and 6(d) (no. of regions: 79), respectively. The result in Fig 6(d) also demonstrates a rough segmentation at the part of the trees and an accurate segmentation at the part of the house.

5 CONCLUSIONS

In this paper we have proposed a method for the segmentation of natural images that integrates the intensity features and the local FD feature into the fuzzy region-growing algorithm. We have estimated the optimum number of the blanket in calculating the local FD by the blanket method. We have investigated the fuzzy-rule based algorithm for integrating different features in the segmentation procedure. Experimental results demonstrates the capabilities of the proposed method to execute the segmentation of natural images with different precision, that is, a rough segmentation at texture regions and an accurate segmentation at non-texture regions simultaneously.

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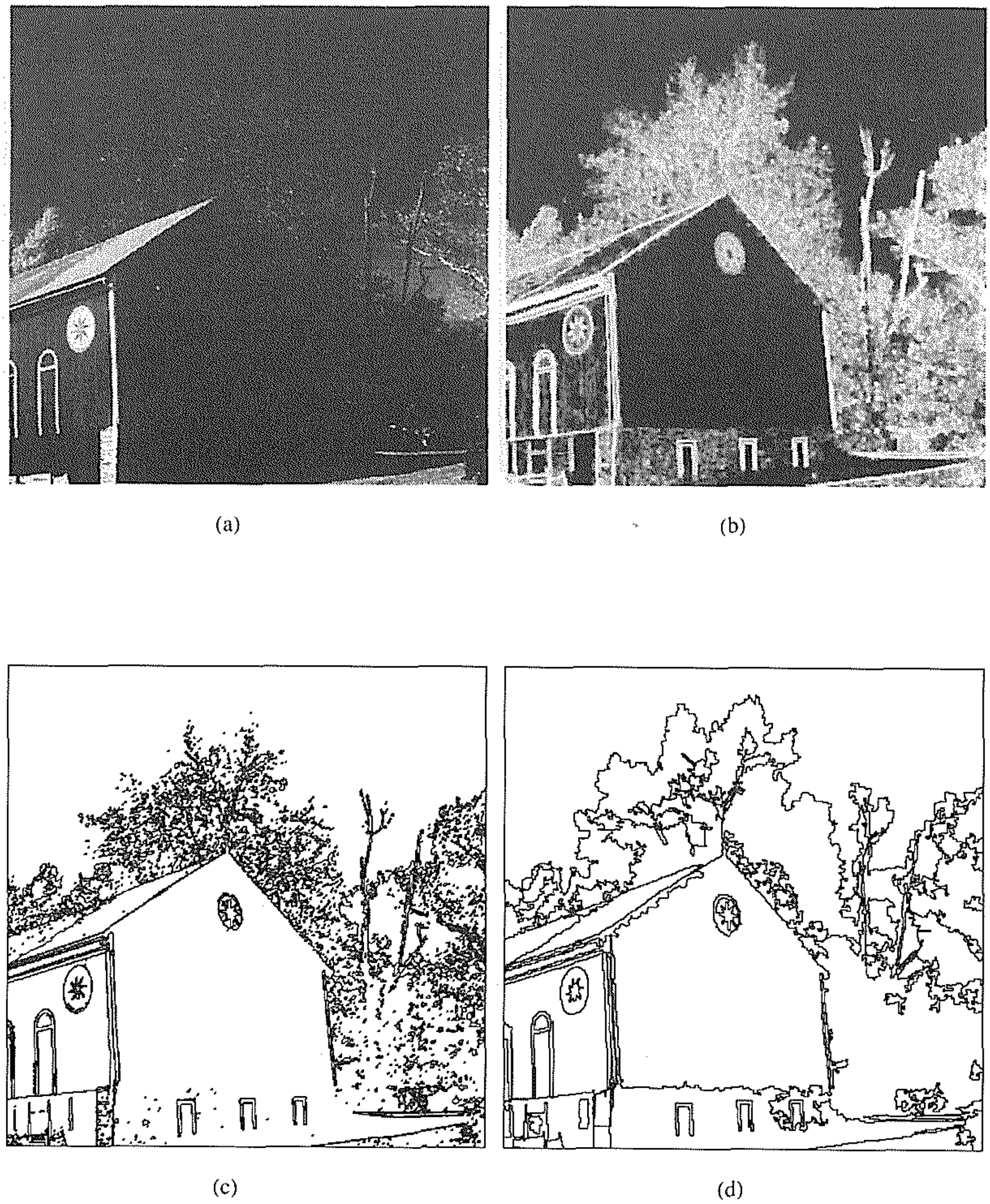
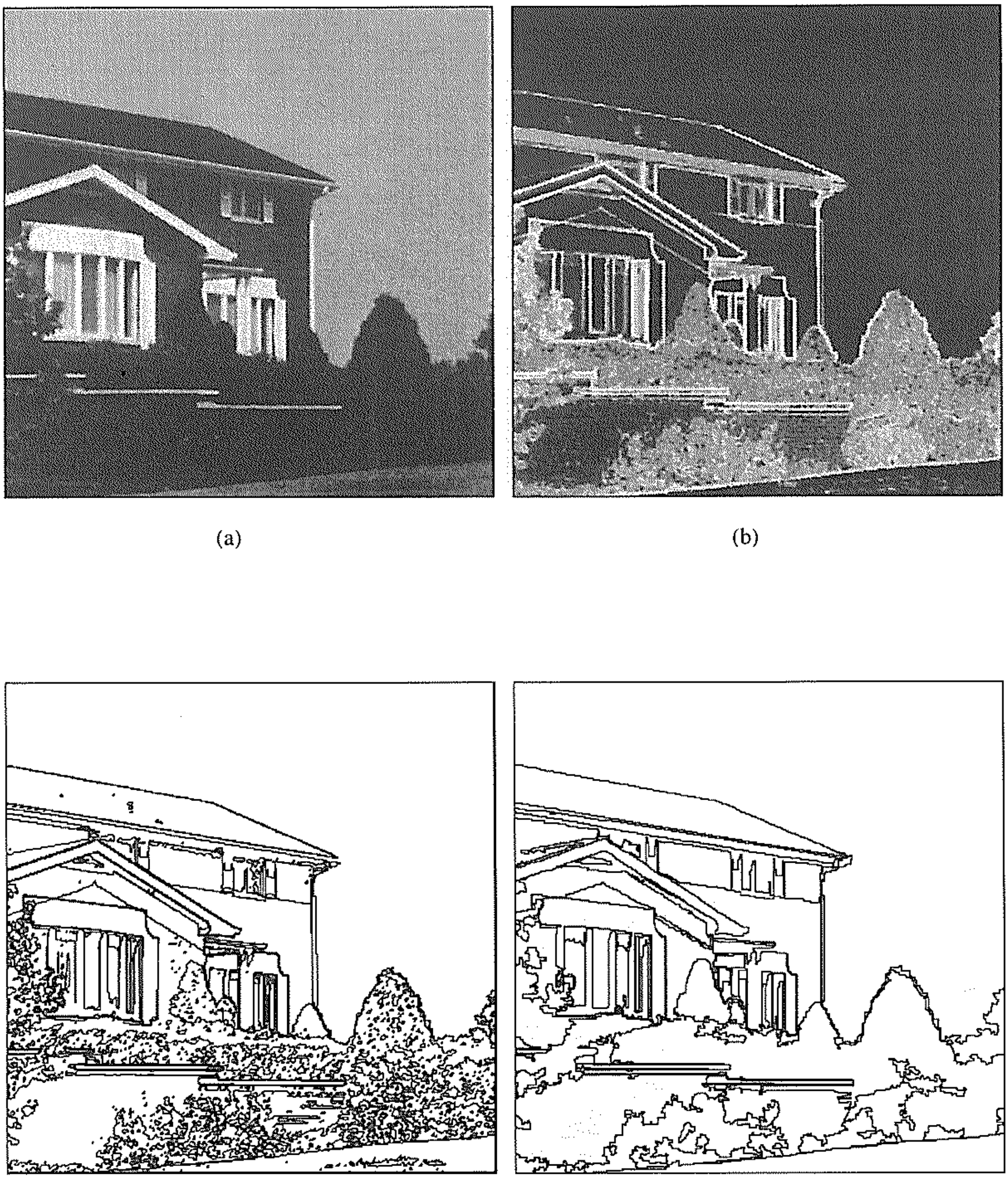


Fig. 5. Experimental results of segmentation for a natural image: (a) original image; (b) local FD map by using the blanket method; (c) segmented image by the conventional region growing algorithm; (d) segmented image by the proposed algorithm.



(a) (b)

(c) (d)

Fig. 6. Experimental results of segmentation for a natural image: (a) original image; (b) local FD map by using the blanket method; (c) segmented image by the conventional region growing algorithm; (d) segmented image by the proposed algorithm.

ファジィ領域成長アルゴリズムを用いた自然画像の領域分割

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概要

我々は、自然画像の領域分割を行うために、濃度階調値と局所的フラクタル次元を領域成長アルゴリズムへと統合する新しい手法を提示している。本手法では、異なるタイプの複数の特徴をひとつの領域分割アルゴリズムへと統合するためにファジィ推論が用いられる。提案手法においては、濃度階調値は自然画像中の精細な領域分割を行うために使用され、局所的フラクタル次元はおおまかな領域分割を実行するために用いられる。異なるタイプの特徴を効果的に組み合わせることにより、人間の視覚系と同様の領域分割結果を得ることが可能となる。実験結果より、ファジィ領域成長アルゴリズムを用いて自然画像の領域分割を実行する提案手法の有効性が検証された。

キーワード：画像の領域分割、領域成長アルゴリズム、ファジィ推論、局所的フラクタル次元、自然画像

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