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Boundary Refined Texture Segmentation Based on K-Views and Datagram Methods*

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***Abstract*-We propose a new texture segmentation algorithm to improve the segmentation of boundary areas in the image. In some applications such as medical image segmentation, an exact segmentation on the boundary areas is needed. But satisfactory segmentation results cannot be obtained on the boundary areas among different texture classes with some existing texture segmentation algorithms in our preliminary experiments. The proposed algorithm consists of three steps. The first step is to apply the K-View-datagram segmentation method to the image to obtain an initial segmentation; the second step is to find a boundary set which includes the pixels with high probabilities to be misclassified by the initial K-View-datagram segmentation; the third step is to apply a modified K-views template method with a small scanning window to the boundary set to refine the segmentation. The evaluation of the proposed algorithm was carried out with the benchmark images randomly taken from Brodatz Gallery and the ultrasonic prostate images provided by the hospitals. Initial experimental results show that the concept of boundary set defined in this paper can catch most of misclassified pixels of the output of the initial K-View-datagram segmentation. The new segmentation algorithm gives high segmentation accuracy and classifies the boundary areas better than the existing algorithms.**

I. INTRODUCTION

Image texture segmentation is an important tool in the computer processing of images such as remotely sensed images and medical images. The most important step for the image texture segmentation is to extract texture features, which can discriminate different types of textures in the image. Many methods have been developed to extract features either using statistics or frequency domain approach [1-14]. Hung et al.[15] presented a texture feature called "characteristic view", which is directly extracted from a sample sub-image corresponding to each texture class. The K-views template method was proposed to classify the texture pixels based on these features. The characteristic view concept is based on the assumption that in an image taken from the nature scenes, a specific texture class in this image will frequently reveal the repetitions of some certain classes of features. Different "views" can be obtained for these features from different spatial locations. Yang and Hung[16] developed the datagram concept and proposed an algorithm using datagrams for texture classification.

If we do not consider the pixels on the boundary among different texture classes, the K-View-datagram algorithm can achieve good segmentation results on most natural images and remotely sensed images [15-16]. But in some applications such as medical image segmentation, an exact segmentation on the boundary areas is needed. Existing texture segmentation algorithms cannot provide satisfactory results for the boundary distinction among different texture classes. We propose a new texture segmentation method in this paper to improve the segmentation of boundary pixels. The proposed algorithm consists of three stages:

1. Apply the K-View-datagram segmentation method to the image as an initial segmentation stage;
2. Find a boundary set which includes all the pixels near the boundary of different texture classes. These pixels are most likely to be misclassified at the initial segmentation stage. The boundary set is defined as a set including all the pixels with more than half of its neighboring pixels being classified into classes other than that of itself at the initial segmentation stage (details are explained in section 3);
3. Apply a modified K-views template method with a small scanning window to the boundary set to correct the misclassifications occurred in stage 1 to obtaining a refined segmentation.

Initial experimental results on the benchmark images randomly taken from Brodatz Gallery [17]+ show that this new segmentation algorithm gives high segmentation accuracy and classifies the boundary areas better than the existing algorithms.

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+ http://www.ux.uis.no/~tranden/brodatz.html

II. Initial Segmentation With the K-View-Datagram Method

First, the K-View-datagram segmentation method proposed by Yang and Hung [16] is applied to the image. The datagram-based algorithm can be described in the following steps:

Step 1: Select a sample sub-image for each texture class from the original image. In other words, N sample sub-images will be selected for N texture classes.

Here a sample sub-image for each texture class is also called a kernel. In this paper, a kernel means an $L\times L$ pixels block, although it can be an $L\times X$ pixels block in the more general case.

Step 2: Extract views from each sample sub-images and form a view set S.

From each $L\times L$ kernel, $(L\text{-}m\text{+}1)^2$ small blocks of size $m\times m$ ($m<L$) can be extracted. We call these small blocks as views. The view set S for a kernel contains all the views of kernel. Apparently, $|S|=(L\text{-}m\text{+}1)^2$. Fig. 1 illustrates a kernel and some of its views.

Step 3: Determine a value k, and use the Fuzzy K-means algorithm to derive a characteristic view set (Cvs) with k characteristic views from the view set S.

A characteristic view set Cvs is a subset of the view set S of the kernel. $Cvs\subseteq S$, $|Cvs|=k$, where k is a chosen constant. Each texture class has a kernel. Each kernel has a Cvs. The Cvs for a texture class represents the sampling features of the texture class.

Step 4: Based on the characteristic view set Cvs, calculate a datagram (D) for each of the N sample sub-images. According to equation 1, normalize each datagram D to a normalized datagram (D_N). We call these N normalized datagrams coming from sample sub-images sample datagrams (D_S).

$$D = (d_1, d_2, d_3, \ldots, d_k)$$
$$T = \sum_{i=1}^{k} d_i \qquad (1)$$
$$D_N = (d_1/T, d_2/T, d_3/T, \ldots, d_k/T)$$

For calculating the datagram D, all the views in the S are classified into k classes according to the Euclid distance between each pair of views that the one is in the S and the other one is in the Cvs. d_i is the number of views whose closest view in the Cvs is the i-th view. Apparently, $T=|S|=(L\text{-}m\text{+}1)^2$.

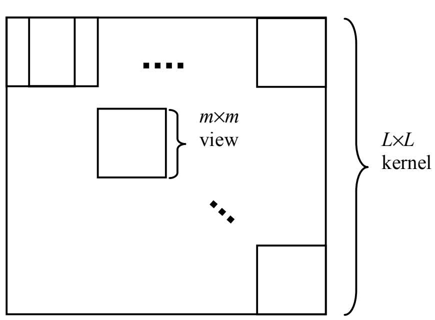


Fig. 1. Some views in a kernel.

Step 5: Scan the whole image using a window of $M\times M$ pixels, and obtain the normalized datagram for each window. Calculate the difference between the normalized datagram and each of the N sample datagrams (D_S), and classify the central pixels of the windows to the class, such that the difference between the sample datagram of the class and the normalized datagram is the minimum difference value. The difference (Dif) between a normalized datagram (D_N) and a sample datagram (D_S) can be obtained by equation (2).

$$D_N = (d_{N1}, d_{N2}, d_{N3}, \ldots, d_{Nk})$$
$$D_S = (d_{S1}, d_{S2}, d_{S3}, \ldots, d_{Sk}) \qquad (2)$$
$$Dif = \sum_{i=1}^{k} | d_{Si} - d_{Ni} |$$

Here M may not be equal to L. For each scanning window with size $M\times M$, there are $(M\text{-}m\text{+}1)^2$ small blocks of size $m\times m$.

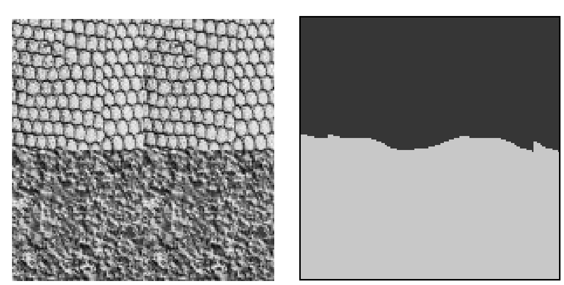
III. Boundary Set

If we do not consider the pixels near the boundary among different texture classes, the K-View-datagram algorithm can achieve good segmentation results on most images taken from nature scenes and remotely sensed images. Fig. 2 shows an example of segmentation results from the initial segmentation stage on a pair of benchmark images taken from Brodatz Gallery.

We can observe from Fig. 2 that the misclassifications are near the boundary of two texture classes. This is because the K-View-datagram method requires a large scanning window; it cannot avoid covering multiple texture classes with the same scanning window.

For example, if a scanning window spans two adjacent texture classes as shown in Fig. 3, its datagram will be influenced by both textures at the upper and lower parts of the window. Hence, it is highly likely that the center pixel of the scanning window will be misclassified.

We define a boundary set for an image and then apply a modified K-views template method with a small scanning



(a) (b)

Fig. 2. (a) An original image and (b) an initial segmentation result of (a).

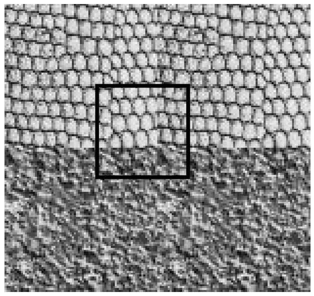


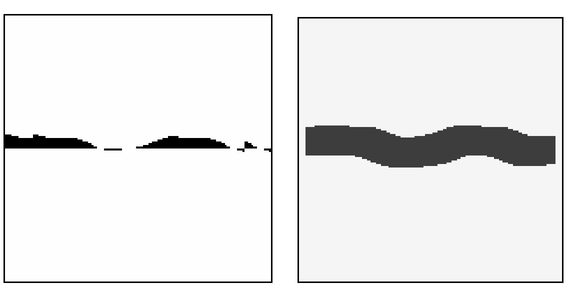
Fig.3. A scanning window spanning two adjacent texture classes.

window to the boundary set to improve the accuracy of the segmentation.

The boundary set B is defined as a set of pixels which includes all the pixels P with more than half of its neighboring pixels being classified into different classes other than those of P itself by the initial K-View-datagram segmentation. Here the neighboring pixel means a pixel within the $n \times n$ square window around the center pixel, where n is an odd integer. Fig. 4 shows the misclassified pixels and the boundary set of the image shown in Fig. 2.

It can be observed in Fig. 4 that almost all the misclassified pixels are included in the boundary set. In the next step, the pixels in the boundary set will be reclassified. It is a natural selection that we choose a small scanning window for our reclassification process. This process will improve the problems associated with the datagram method. We design a modified K-View template method for boundary pixels refinement.

IV. Boundary Refinement with a Modified K-View Template Method



(a) (b)

Fig. 4. (a) Misclassified pixels and (b) the boundary set B of the image in Fig. 2.

After the boundary set is found, a modified K-view template segmentation algorithm is applied to it with a small scanning window to reclassify those pixels of the boundary set. In the original K-view template algorithm proposed by Hung et al.[15], each pixel is classified into the class with its characteristic view set has the most similar view to the characteristic view set of that class. In our modified K-view template algorithm, each pixel in the boundary set has a candidate class set associated with it. The neighboring pixels of a pixel P can only be reclassified into the classes appearing in the corresponding candidate class set of P.

The candidate class set for a pixel is defined as the set of the classes assigned to its neighboring pixels by the initial K-View-datagram segmentation. For example, suppose that an image contains four classes of textures; say class A, B, C and D. A pixel P in the boundary set is classified into class A, by the initial segmentation, and more than half of its neighboring pixels are classified into other classes such as class B, but no pixel in its neighboring areas is classified into classes C and D. Then the candidate class set for pixel P is $\{A, B\}$. The pixel P can only be reclassified into class A or B in the following refinement stage. It cannot be reclassified into classes C and D.

This is reasonable on the assumption that whatever a pixel P in the boundary set is properly classified or misclassified at the initial segmentation stage, at least one of its neighboring pixels which actually belong to the same class with P should be properly classified. In the most cases, this assumption is true. So the real class of P should appear in the candidate class set of P. In other words, those unlikely classes for P should be excluded from the candidate set of P by this definition.

The procedure of the modified K-Views Template algorithm is described in the following.

Step 0: Suppose N kernels of the original image is determined in the initial segmentation stage. The boundary set B is also determined by the boundary set setting stage.

Step 1: For each pixel P in the boundary set B, determine a candidate class set for P.

Step 2: For a smaller view size $w \times w$ ($w \leq m$), extract a view set from each kernel of the original image.

Step 3: Determine a new value of k for each view set, and derive k-views of characteristic view set from each kernel using the fuzzy k-means algorithm. k may vary for each texture class (i.e. kernel). Now each characteristic view set corresponds to a texture class in the original image.

Step 4: In the pixel reclassification process, for each scanning window of size $w \times w$, say W, of the pixel P in the boundary set B being reclassified, find a characteristic view that best matches the scanning window W in all the characteristic view sets that their corresponding classes belong to the candidate class set of P.

Step 5: If the best-matched characteristic view belongs to characteristic view set corresponding to class C, classify the pixel P to class C.

Step 6: Repeat steps 4 and 5 for each pixel in the boundary set B being reclassified.

V. EXPERIMENTAL RESULTS

The evaluation of the algorithm on the benchmark images which are randomly selected from Brodatz Gallery [17] was carried out.

At the initial segmentation stage, when the K-View-datagram method is used, a large k value and a reasonable kernel size and view size must be chosen in order to have high segmentation accuracy in the non-boundary areas. Otherwise, the characteristic view set would not be powerful enough to classify image texture in the non-boundary areas. We chose k=60, which is the number of views in each characteristic view set. The size of kernel was chosen as 40×40 (L=40), the size of view was chosen as 10×10 (m=10), the size of scanning window was chosen as 30×30 (M=30), which is smaller than the size of kernel but is still large enough.

At the boundary set searching stage, n=11 is chosen. It means that we consider the pixels in the square block of size 11×11 around a pixel as its neighboring pixels. At the refinement stage, when the modified K-Views template method is applied, a different k value and a smaller view size are chosen in order to have high segmentation accuracy in the boundary set. We chose k=30, and the size of view was set to 7×7(w=7) for this stage.

Table 1 shows the experimental results conducted on 80 combined texture images. Each combined image consists of two to five benchmark texture images randomly chosen from the Brodatz Gallery. 80 combined texture images can be divided into 4 groups according to the number of benchmark images; they consist of 2, 3, 4 and 5 textures, respectively. Each group has 20 combined texture images. The segmentation accuracy is defined as the ratio of the number of properly classified pixels to the total number of pixels in the image.

TABLE I
AVERAGE SEGMENTATION ACCURACY CONDUCTED ON EIGHTY COMBINED TEXTURE IMAGES

Number of texture classes in an image	2	3	4	5
Initial accuracy	98.2%	97.0%	91.7%	90.9%
Refined accuracy	98.9%	98.2%	95.4%	94.8%

Fig. 5 shows the boundary refined segmentation result for a combined image consists of 5 benchmark texture images. As shown in Fig. 5, (a) is the original image; the initial segmentation result shown in (b) is good in the non-boundary areas, but many pixels near the boundary are misclassified. (c) shows the boundary set B calculated at the boundary set setting stage according to our definition; (d) shows the misclassified pixels and it can be observed that the misclassified pixels are all around the boundary; (e) shows the refined segmentation result and (f) shows the remaining misclassified pixels after the refinement operations. It can be seen that the result shown in (b) is improved comparing with the result shown in (e).

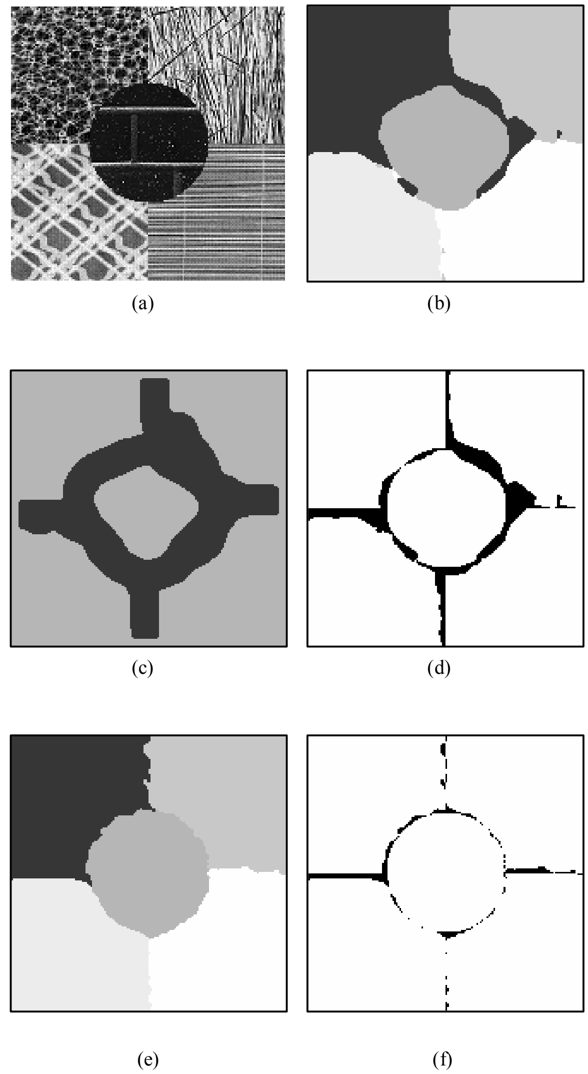
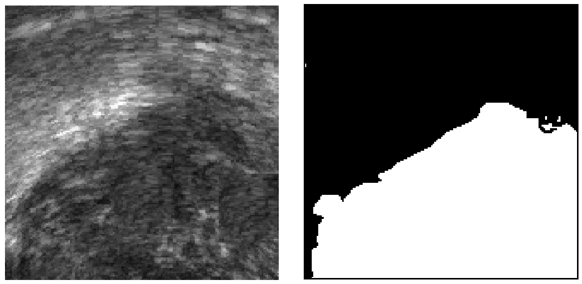


Fig. 5. (a) An original image with textures, (b) the initial segmentation result, (c) the boundary set, (d) pixels misclassified by the initial segmentation, (e) the refined segmentation result and (f) pixels still misclassified after the refinement of the segmentation.

The most common technique for the diagnosis of prostate cancer is core biopsy using ultrasound images [18]. The adult prostate is a chestnut-shaped organ enveloped in a fibrous capsule. Ultrasound images can help identify areas of hypoechogenicity that may not be palpable, thus leading to more accurate sampling of the prostate. Transrectal ultrasonography (TRUS) guided core biopsy is routinely used clinically. A number of researchers have investigated techniques for improving the accuracy of biopsy protocols. Automatic or interactive segmentation of the prostate in



(a) (b)

Fig.6. (a) An original ultrasonic prostate image and (b) final segmentation result: White: prostate; Black: other tissues.

ultrasonic prostate images is an important step in these techniques [19].

Our new segmentation algorithm provides an automatic method for this work. But in practice, a mass of noises existed in the ultrasonic prostate images, so a small adjustment is applied to the formula for calculating the distance between two views to overcome this problem. That is, we no longer to calculate the Euclid distance of two views directly as we did before, but first to sort the pixel values in each view, and then to calculate the Euclid distance on the ordered pixel values of the two views. The experimental results show that the new segmentation algorithm gives satisfactory segmentation accuracy. Fig. 6 shows an initial experimental result for an axial ultrasonic prostate image.

VI. CONCLUSIONS

Some of existing image texture segmentation algorithms cannot provide satisfactory results on the segmentation of boundary areas among different texture classes. If we do not consider the pixels on the boundary areas, the K-View-datagram algorithm can achieve good segmentation results on most images taken from nature scenes and remotely sensed images. But in some applications such as medical image segmentation, high segmentation accuracy on the boundary areas is needed. The boundary set concept defined in this paper can catch almost all misclassified pixels propagated from the initial K-View-datagram segmentation stage. A small scanning window is used in the modified K-View template algorithm for the boundary pixels reclassification process.

Preliminary experimental results show that the new segmentation algorithm gives higher segmentation accuracy and classifies the boundary areas better than that of the K-View-datagram algorithm.

Extensive experiments on the proposed algorithm need be completed for different types of texture images. Generalizing the method to a typical multi-resolution approach will be explored.

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