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中文摘要

本研究計畫運用小波轉換理論來進行紋理分離的研究。基本上，這類研究所必須處理的議題包括下列三點:

1. **如何自分解所得的子影像中擷取適當的紋理特徵。**
2. **如何剔除不具資訊的子影像以加快分離的速度及正確性。**
3. **如何整合各子影像的紋理特徵以達到分離的目的。**

為解決上述議題，本計畫利用同一紋理區域內的影像點必和其鄰近點相似之特性，提出一基於小波轉換的紋理分離方法。此方法的特色在於能在不運用任何紋理特徵的前提下將紋理區域順利分離出來。首先我們將對原圖施以小波轉換以分解成不同頻率和方向的子影像。再利用多值閥值化之技巧將各子影像分成不同的紋理區域。在此階段中，若某子影像只含一區，則在後續的分離步驟中將不予考慮，以加快分離的速度及正確性。接著我們利用前述所提之特性提出一個子影像區域整合的方法，此方法將整合各子影像的分區結果,進而將各紋理區域之內部與邊界分離以達到初步的分離效果。最後再對邊界上的影像點我們再運用一個分類的技術將之一一歸屬於各紋理區域以完成整個分離的動作。我們進行各式實驗以驗證方法的正確性及效能。

關鍵詞：紋理分離、小波轉換、多解析度分離、無監督式分群

Abstract

Traditional approaches for texture segmentation via wavelet transform usually adopt textural features to achieve segmentation purposes. However, for a natural image, the characteristics of the pixels in a texture region are not similar everywhere from a global viewpoint, over-segmentation often occurs. To deal with this issue, an unsupervised texture segmentation method based on determining the interior of texture regions is proposed. The key idea of the proposed method is that if the pixels of the input image can be classified into interior pixels (pixels within a texture region) and boundary ones, then the segmentation can be achieved by applying region growing on the interior pixels and reclassifying boundary pixels. Based on the fact that each pixel *P* within a texture region will have similar characteristics with its neighbors, after applying wavelet transform, pixel *P* will have similar response with its neighbors in each transformed subimage. Thus, by applying a multi-level thresholding technique to each subimage to segment the subimage into several regions, pixel *P* and its neighbors will be assigned to the same region in most subimages. Based on these segmented results, an interior pixels finding algorithm is then provided to find all interior pixels of textural regions. The algorithm considers a pixel which is in the same region as its neighbors in most subimages as an interior pixel. The effectiveness of this method is proved by successfully segmenting natural texture images and comparing with other methods.

Keywords: Texture segmentation, Wavelet transform, Multiresolution segmentation, Unsupervised clustering

Introduction

Texture segmentation has long been an important topic in image processing. Basically, it aims at segmenting a textured image into several regions with the same texture features. An effective and efficient texture segmentation method will be very useful in applications like the analysis of aerial images, biomedical images and seismic images as well as the automation of industrial applications. Like the other segmentation problems, the segmentation of textures requires the identification of proper texture-specific features with good discriminative power. Generally speaking, texture feature extraction methods can be classified into three major categories, namely, statistical[1-3], structural[4-5] and spectral[6]. In addition to the aforementioned methods, Law's texture energy measures[7], Markov random field models[8], texture spectrum[9] etc. are some other texture descriptors.

Recently, multichannel and multiresloution-based approaches have drawn lots of attention in the field of texture analysis. Several successful applications of these approaches to unsupervised texture segmentation have been reported. Multichannel-based approaches[10-12] use a bank of pre-selected Gabor filters in terms of frequencies, orientations and bandwidths to filter an input image. The features extracted from the responses of the filtered images are then used for texture classification or segmentation. Wavelet transform is used in multiresolution-based approaches. Most of the wavelet-based methods[13-15] use a pyramidal type of decomposition to transform the input image into an image of wavelet coefficient at different resolutions. The wavelet coefficients are then transformed into texture-specific features. Based on the features, traditional clustering techniques such as c-means[16] are adopted to segment the image into texture regions. Then, the segmentation results under different resolutions are further integrated to produce final segmentation result. For a natural texture, however, the characteristics of the pixels in the texture pattern are not similar everywhere from a global viewpoint. Thus, without using a good integration technique for the feature images resulted from wavelet transform, over-segmentation often occurs for these methods.

To circumvent the above-mentioned issue, in this project, based on the fact that each interior point in a texture region must possess similar properties with its neighbors, a new wavelet-based texture segmentation method is proposed. The key idea is that if the pixels of the input image can be classified into interior pixels and boundary ones, the interior pixels stand for the interior parts of texture regions, then the segmentation can be achieved by applying region growing on the interior pixels. To implement this idea, a wavelet transform is first applied to get several subimages with different frequencies and orientations. Then, in each subimage, the wavelet coefficients are thresholded to get preliminary segmented results. As each pixel within a texture region will have similar response with its neighbors in the transformed images, it will be assigned to the same region as its neighbors in most subimages. An interior pixels finding algorithm is then provided to integrate the segmented results of the subimages to separate texture interiors from their boundaries. Texture regions can therefore be extracted by region growing. Finally, the texture boundaries are reclassified and segmentation is achieved.

Experimental Results and Discussion

Our method has been tested on several textured images from Brodatz album[15] and a natural image. All images used have 256x256 pixels and are gray-scale ones. Packet-structured wavelet transform is used up to two levels in all experiments. Besides, for the comparison purpose, the same set of images are tested using the methods proposed in [12] and [19] as well. Fig. 1 shows the segmentation results for an image which consists of three texture regions. The processing result of each step of our method is shown by sequence. Fig. 1(c) shows the multi-level thresholded and region-edited image with some homogeneous sub-images. As these homogeneous sub-images do not provide useful information for segmentation, they are excluded from later processing steps to accelerate the computation.. It is noticed that some texture regions are segmented successfully in some subimages. But, it is hard to find a single subimage with satisfactory segmentation result. By integrating the segmentation results from subimages via finding the interior pixels, three textures can finally be obtained. As seen from the segmentation result in Fig. 1(d), three textures are successfully segmented, and the result is quite accurate. Figure 1(e) shows the result of applying the method proposed in [12], some pixels of the straw texture are mis-classified and produce small regions. Besides, boundary pixels of the three textures are mis-classified either, and segmented into another region. On the other hand, Fig. 1(f) shows the over-segmented result of [19], which segments Fig. 1(a) into four regions.

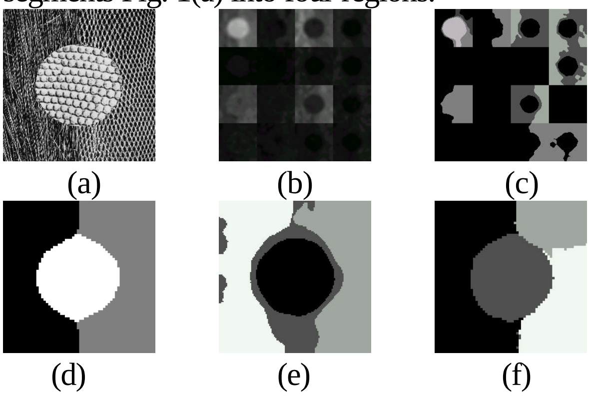

Fig. 1. Segmentation results of the proposed method and methods in [12] and [19] for a three-category Brodatz textures.

Fig. 2(a) shows another textured image obtained by collaging four Brodatz textures. Fig. 2(b) shows the segmentation result which successfully separate these four texture patterns. Fig. 2(c) shows the result of [12], the pixels of the boundary areas between texture patterns are mis-classified. The result of [19] is shown in Fig. 2(d), it is roughly comparable to that of the proposed method.

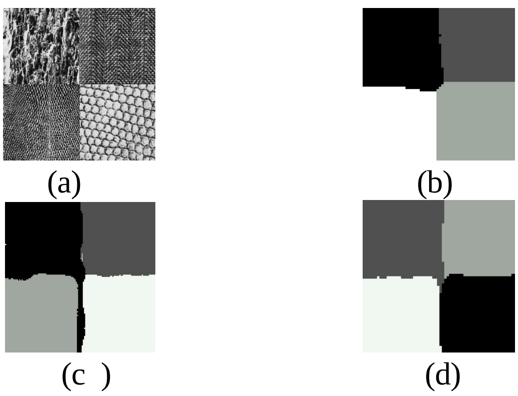

Fig. 2. Segmentation results of the proposed method and methods in [12] and [19] for a four-category Brodatz textures.

Fig. 3(a) shows a five-category textured image. The left and right patterns are very similar in terms of intensity and texture pattern. Fig. 3(b) shows the segmentation result of the proposed method and the result is satisfactory. Fig. 3(c) shows the result of [12], which wrongly classifies the boundary pixels and makes the boundary pixels merged with the texture pattern on the left. Fig. 3(d) shows the result obtained by [19], it is roughly comparable to that of Fig. 3(b).

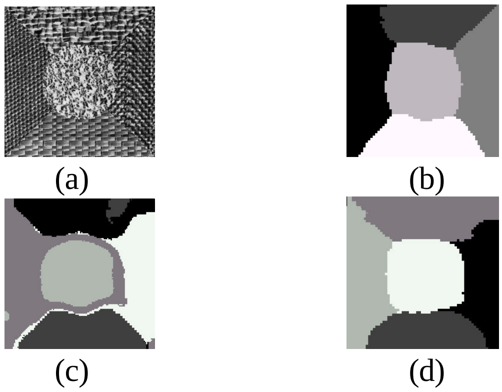

Fig. 3. Segmentation results of the proposed method and methods in [12] and [19] for a five-category Brodatz textures.

Fig. 4(a) shows a natural image containing three zebras. The position of zebras is correctly extracted by the proposed method and shown in Fig. 4(b). Fig. 4(c) shows the result obtained by applying the method proposed in [12], which cannot correctly extract the position of the three zebras. Result obtained by [19] is shown in Fig. 4(d), the zebras are not segmented out successfully.

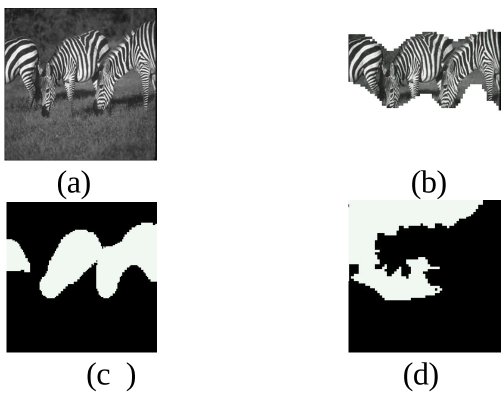

Fig. 4. Segmentation results of the proposed method and methods in [12] and [19] for a

natural image with three zebras.

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