WATERSHED-BASED TEXTURAL IMAGE SEGMENTATION

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ABSTRACT

The watershed transform is a well-established tool for image segmentation. However, watershed segmentation is often not effective for textural images. In this paper, we describe an improved watershed segmentation algorithm combined with texture features. The aim of this study is to improve the generalization of watershed techniques and to construct a well segmentation of textural images. The method includes two stages. The first stage is standard watershed algorithm. The second stage is processed by a clustering algorithm, fuzzy c-means (FCM). Watershed algorithm provides small homogenous patches which are merged by clustering algorithm based on texture features. The experimental results demonstrate that the combined algorithm is effective for textural image segmentation.

Index Terms— image segmentation, texture, watershed

1. INTRODUCTION

Image segmentation is an important and, perhaps, the most difficult task in image processing. Segmentation refers to the grouping of image elements that exhibit "similar" characteristics, i.e. subdividing an image into its constituent regions or objects. All subsequent interpretation tasks, such as object recognition and classification, rely heavily on the quality of the segmentation process. Most segmentation techniques have been applied to the simple case for which the definition of "homogeneous" is based on a single gray-level characteristic. Some of these techniques have been extended for the use of multiple features and applied to the more difficult problem of segmentation based on texture. All these techniques may be classified into a number of groups, including feature threshold, contour based techniques, region based techniques, clustering, template matching, etc [1]. Each of these approaches has its own merits and demerits in terms of applicability, suitability, performance, computational cost etc. Compared to gray-level based approaches, these texture-based methods are faced with more difficulties and many methods available can not consistently and accurately segment textural images.
The watershed transform is a well-established tool for the segmentation of images based on gray levels. Over segmentation is a major problem with watershed transform, which has led to a number of approaches including marker based watershed segmentation [2], region merging [4], hierarchical watersheds [1], morphological filtering [5], [6] and the algorithm that is combined watershed algorithm with spectral clustering algorithm [3], for image segmentation. Actually the idea of the method [3] is region merging.
Vital information characterizing texture can be lost in the smoothing operation, that is, gradient of watershed segmentation method. So watershed algorithm is often not effective for textural images. In order to improve the generalization of watershed techniques, we show an improved watershed algorithm by referring to that in paper [3]. The new algorithm adds a useful cluster stage and makes use of texture features. Experiments show that it is more effective to textural image segmentation.
The paper is organized as follows. Section 2 provides the necessary background on watershed segmentation. In section 3 the proposed method is presented. Section 4 demonstrates the practical utility of the approach, followed by conclusions and future avenues of investigation as discussed in section 5.

2. WATERSHED TRANSFORMATION

The idea of watershed is drawn from a topographic analogy. Quite naturally the first algorithm for computing watersheds is found in the field of topography [9]. The introduction of the watershed transformation as a morphological tool is due to Digabel et al [10]. Watershed is then approached theoretically by F. Maisonneuve and used in numerous grayscale segmentation problems. Currently, it is being studied from theoretical, practical, and algorithmic points of view.
The watershed transform applied to the image does not produce contours of the features. On the contrary, it partitions the image into the associated areas by the intensity gradient and considers the gradient image as a topographic relief, where the intensity of a pixel denotes the altitude of that pixel. Each pixel in this digital image is assigned a label during the transformation of the catchments basin of a regional minimum. When finished, the resulting network of dams defines the watershed of the image. Compared to the other methods, the watershed has several advantages as follows [2], [7]:

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– The gaps are handling properly and the placement of boundaries is at the most significant edges.
– The resulting boundaries form closed and connected regions.

The disadvantage is that for textural images the watershed transformation does not use of texture information and produces excessive over-segmentation. The reason is that the image contains a lot of texture information that bring in too much seeds. So we adopt a two-stage method for textural image segmentation. The first stage uses standard watershed algorithm. The second stage is processing by a clustering algorithm, fuzzy c-means (FCM).

Cluster analysis is a tool for clustering a data set into groups of similar characteristics. Since Zadeh [11] proposed fuzzy sets, which produced the idea of partial membership described by a membership function, fuzzy clustering has been successfully applied in various areas such as feature analysis, pattern recognition, image processing, medical engineering, classifier design, clustering, neural networks, etc[8]. In fuzzy clustering, the fuzzy c-means (FCM) algorithm plays an important role and it has perfect theory foundation. Here we adopt FCM to perform the final segmentation.

3. IMPROVED ALGORITHM

An image can be segmented into classes based on gray levels, textures, edges, etc. The watershed transform is the algorithm, which based on gray levels. For textural images, however, the texture information of them complicates the characteristics of the image and results in over segmentation with homogeneous texture regions. In order to compensate for the weakness, two-step approach for textural images segmentation is proposed, which aims to construct a well segmentation of the textural images. First, watershed algorithm is applied to segment the images. Then, the watershed over-segmentations results with small homogenous patches are merged with clustering algorithm based on texture features. In the following, we first need to characterize the textural content of the image at each block, i.e. texture features extraction.

3.1. Gray Level Cooccurrence Matrix

Texture involves the spatial distribution of gray levels in a local region. It contains important information about the structural arrangement of surfaces and their relationship to their neighboring surfaces. A common technique in texture analysis involves the computation of Gray Level Cooccurrence Matrix (GLCM) as a second-order texture measure. GLCM describes the frequency of one gray tone. Several statistical parameters can be extracted from GLCM. Some of these parameters are related to specific first-order statistical concepts, such as contrast and variance, and have a clear textural meaning. Other parameters contain textural information but associated with more than one specific textural meaning [12]. Four textural parameters, energy, entropy, correlation and inverse difference moment, are used here.

Energy measures textural uniformity. High energy values occur when the gray level distribution over the window has either a constant or a periodic form.

$$ene = \sum_{i=1}^{N}\sum_{j=1}^{N} g^2(i,j) \tag{1}$$

Entropy measures the disorder of an image. When the image is not texturally uniform, many GLCM elements have very small values, which imply that entropy is very large.

$$ent = -\sum_{i=1}^{N}\sum_{j=1}^{N} g(i,j)\cdot\log(g(i,j)) \tag{2}$$

GLCM Correlation is expressed by the correlation coefficient between two random variables i and j, where i represents the possible outcomes in gray tone measurement for the first element of the displacement vector, while similarly j is associated with gray tones of the second element of the displacement vector. Correlation is a measure of gray tone linear-dependencies in the image. High correlation values (close to 1) imply a linear relationship between the gray levels of pixel pairs.

$$cor = \sum_{i=1}^{N}\sum_{j=1}^{N} (i-\mu)\cdot(j-\mu)\cdot g(i,j)/\sigma^2 = \frac{\overline{\Delta_{cor}}}{\sigma^2} \tag{3}$$

Inverse Difference Moment also called homogeneity. This parameter measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements. Therefore, the parameter is more sensitive to the presence of near diagonal elements in the GLCM.

$$idm = \sum_{i=1}^{N}\sum_{j=1}^{N} \left[1/(i+(i-j)^2)\right] g(i,j) = \overline{\Delta_{idm}} \tag{4}$$

where $\Delta_{idm} = \dfrac{1}{1+(i-j)^2}$.

3.2. Wavelet Feature

The notion of scale is an important concept to texture analysis. Recently, wavelet transform has received much attention as a promising tool for texture analysis, because it has the ability of examining a signal at different scales. The two-dimensional (2-D) wavelet transform decomposes an image into four sub-images. Fig.1 shows the ordinary dyadic decomposition. The approximated image LL is obtained by low-pass filtering in both row and column directions. The detail images, LH, HL, and HH, contain high frequency components.

The texture feature set is made up of the Energy and Mean Variance of decomposed coefficients.

$$mv = \frac{1}{N^2}\sum_{k=1}^{N}\sum_{l=1}^{N} \left| w(k,l) - \overline{w}(i,j) \right| \tag{5}$$

where $w(k,l)$ denotes the wavelet coefficients of a sub-image in the N×N window centered by pixel (i, j).

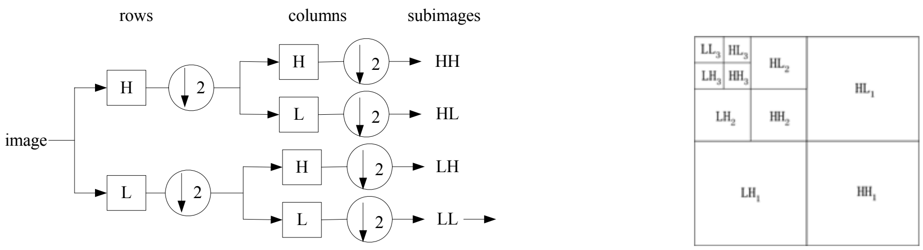


Fig. 1. 2-D wavelet transform.

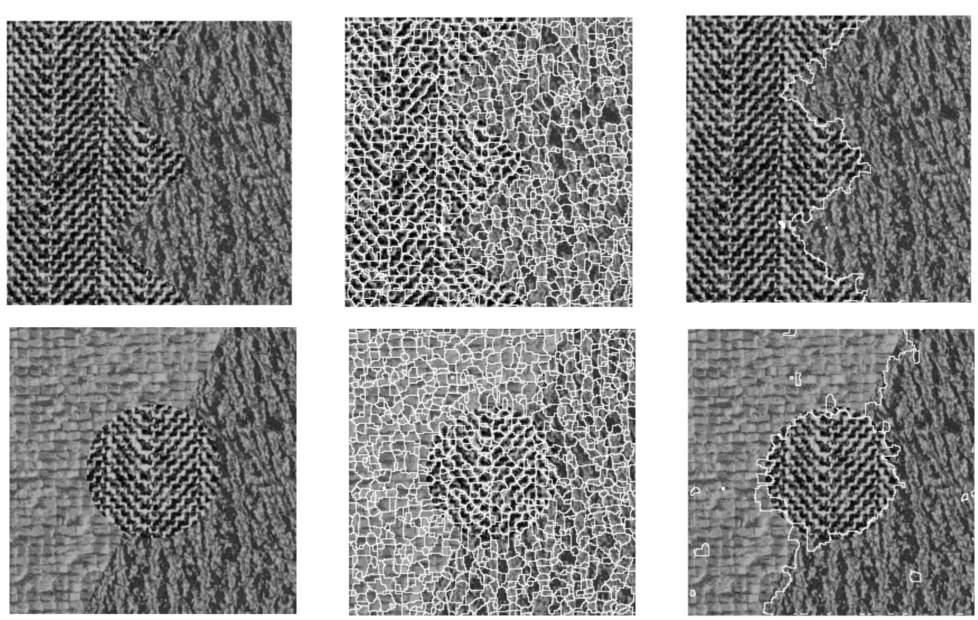
GLCM is an effective tool for texture feature extraction. It is controlled by partial parameters and can extract texture feature from many directions. While wavelet is a global transform. It has better characteristic of time-frequency analysis and can analyze and represent the textural structure from different scales. The two features can compensate for each other. Obviously, combining different texture features above is helpful to improve the segmentation accuracy. However, it is impossible to directly extract the textural feature from irregular block using grey matrix and wavelet owing to the irregular shape over-segmented by watershed algorithm. Therefore, we extract the textural feature vectors from neighbors of the pixel, and then use the mean value as the feature of irregular block.

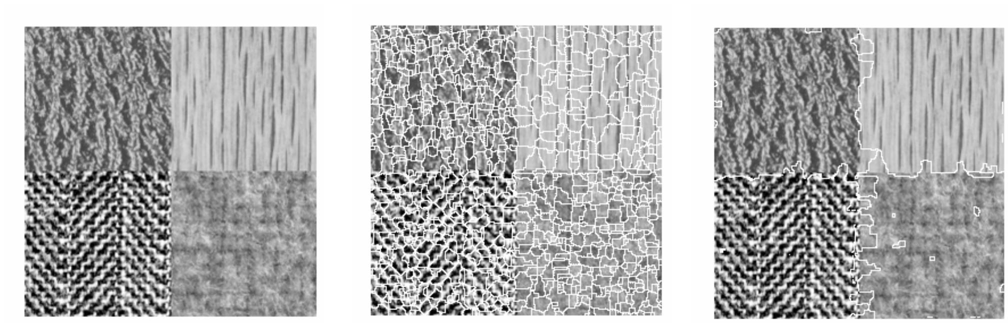
4. EXPERIMENTAL RESULTS AND DISCUSSIONS

The proposed algorithm has been executed on a set of texture images, which were created by combining original texture images taken from the Brodatz album. Some of the test images used in the experiment are shown in Fig.2a to Fig.4a. The segmentation results of the proposed algorithm and watershed algorithm are shown in (b) and (c) Fig.2. The average number of block and statistical error rate of the segmentation results of different methods are shown in Table.1. In addition, GLCM feature vectors are extracted for the center pixel in a certain window region of size 5×5. The wavelet features are extracted from 16×16 region windows.

In comparison with the initial segmentation results of watershed algorithm, the edges obtained by the proposed method are quite close to the real edges and the error rates are very low. But it can be seen that some sham edges around the real edges are present in the segmentation results. This can be explained by the inaccurate gradient of watershed segmentation. How to solve this problem effectively needs our future research.

From Table.1, we can see that the block number and error rate of the method on wavelet feature are lesser than that of the proposed method. This means that sometimes certain features not only are redundant but also can disturb the segmentation. So feature selection is another good problem in the future.





(a) original texture image (b) watershed initial segmentation (c) final result

Fig. 2. Illustration of the segmentation algorithm.

Table 1. Result of Fig.2: Average block number and error rate

		Watershed	The Method	Wavelet Feature	GLCM Feature
Class 2	Block number	901	12	3	55
	Error rate (%)	--	3.00	2.53	5.84
Class 3	Block number	876	7	20	10
	Error rate (%)	--	4.47	6.71	7.93
Class 4	Block number	838	19	23	68
	Error rate (%)	--	5.79	6.81	9.88

5. CONCLUSION

In this paper, a method for improving the quality of the textural images segmentation based on watershed was proposed. It relies on the second processing stage, for patches clustering. Two methods have been used during texture feature extraction. Our preliminary results show that the proposed technique is robust to textural images segmentation.

However, further research is necessary to concentrate on feature extraction, such as the application of the multiscale geometry analysis including ridgelet analysis, curvelet, brushlet and etc. These methods may be more effective to characterize the texture features of an image.

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