Unsupervised segmentation Algorithm based on fusion of multiresolution features

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Abstract— This paper presents the development of an unsupervised image segmentation using the multi-resolution analysis technique. An important contribution of this work consists of combining gabor filters and wavelet. Texture analysis is done using a bank of filters and many features are computed using texture decomposition with the aim of identifying the homogenous regions in the image. The system builds Features vector for each pixel that contains information about the gray level, and other texture information. These vectors are used as inputs for the K-means clustering method, which results a segmented image whose regions are distinct from each other according to texture characteristic content. To evaluate the performance of this analyze we applied the methodology to a brodatz database and to MSG images.

Index Terms— Gabor filters, Segmentation, texture, wavelet

I. INTRODUCTION

TYPICAL computer vision applications usually require an image segmentation processing algorithm as a first procedure. At the output of this stage, each object of the image, represented by a set of pixels, is isolated from the rest of the scene.

The extraction of features that are sensitive to texture in an image has been the subject of intensive investigations in recent years [1], [3], [5]. Some of the most popular texture feature extraction methods are based on the gray level co-occurrence statistics [6], edge gradients [7], filtering methods like morphological filters, Fourier filters, random field models [8], fractal dimension [9], local binary patterns [10]. Gabor filters [11], and wavelet decomposition approaches [12]. Each method is superior in discriminating its texture characteristics, there is no universal method available for all textures.

The development in multiresolution analysis such as wavelet transform leads to the development of adequate tools to characterize different scales of textures effectively. On the other hand, the orthogonality of discrete wavelet offers an efficient filtering implementation with relatively poor directional properties. The wavelet transform lacks in its ability to decompose input image into multiple orientations. Gabor filters have been recognized as a joint spatial/spatial-frequency representation for analyzing textured images that contain highly specific frequency and orientation characteristics. The Gabor filter banks are not mutually orthogonal, which may result in a significant correlation among texture features. Gabor transform performs somewhat better than wavelets. This is because of its optimality in space–frequency localization and the flexibility in choosing directions per radial frequency band.

The proposed method, based on the multiresolution analysis, consists of combining gabor filters and wavelet, with the goal to exploit advantages of these two methods. This paper is organized as follows. In the next two sections, dyadic wavelet decomposition and gabor filters briefly reviewed. Section 4 describes the feature extraction step. In section 5 the segmentation results of the combination of those two methods are presented. The last section gives some concluding remarks.

II. WAVELET MULTiresOLUTION ANALYSIS

The wavelet transform module constitutes a step of image segmentation with the objectives of extracting texture features. The simplest way to compute 2D DWT of an image is to apply one-dimensional transforms over image rows and columns separately and downsampling. In practice, dyadic wavelet decomposition is carried out using 2channel filter banks composed of a low-pass (L) and a high-pass (H) filter and each filter bank is then sampled at a half rate (1/2down sampling) of the previous frequency. By repeating this procedure, it is possible to obtain wavelet transforms of any order [6].

Through the wavelet decomposition on an appropriate scale, produces an approximation and three detailed images, which contain fine structures in horizontal (LH subband), vertical (HL subband) and diagonal (HH subband)
orientations. An example of one-level decomposition of an image is shown in Fig. 1.

The wavelet image decomposition provides a representation that is easy to interpret. Every subimage contains the information of a specific scale and orientation. The decomposition conveniently separates the information of different scales. To obtain features that reflect scale-dependant properties, one can extract them from each subimage separately. The result depends on the type of the wavelet on which decomposition is based on, which in turn depends on the filter specifications. The determination of a proper multiresolution level is crucial and affects the result of the segmentation.

III. GABOR FILTERING

A 2-D Gabor filter acts as a local band-pass filter with certain optimal joint localization properties in the spatial domain and in the spatial frequency domain. Given an input image I(x,y), Gabor transform is performed by convolving I(x,y) with a set of Gabor filters of different orientation and spatial frequencies that cover appropriately the spatial frequency domain. The general functional of the two-dimensional Gabor filter family can be represented as a Gaussian function modulated by an oriented complex sinusoidal signal.

A set of Gabor filters of different scale and orientation is convolved with an image to estimate the magnitude of local sinusoidal signal. We have used even-symmetric Gabor filters. For our study, given by:

\[ h(x, y, \mu, \theta) = \exp \left( -\frac{1}{2} \left( \frac{x'}{\sigma_x} \right)^2 + \left( \frac{y'}{\sigma_y} \right)^2 \right) \cos(2\pi \mu x') \]

(1)

where \( x' = x \cos \theta + y \sin \theta; \) \( y' = -x \sin \theta + y \cos \theta; \) \( \mu \) is the frequency of the sinusoidal wave along the direction \( \theta \) from the \( x \)-axis; \( \sigma_x \) and \( \sigma_y \) specify the Gaussian envelope along \( x \) and \( y \)-axis, respectively, which determine the bandwidth of the Gabor filter.

IV. TEXTURE FEATURES

Textural features are extracted from wavelet-decomposed and gabor-filtered images and used for classification, with the aim of identifying the homogenous regions in the image. One must take into account a neighborhood of each pixel since texture is not a local phenomenon. The feature at a pixel \((x, y)\) is calculated within the local window of size \(N \times N\) centered at this pixel. The local window size should be properly controlled for the exact texture segmentation.

It is, therefore, necessary that the size of the wavelet detail subbands should be the same as that of the original image. We obtain this by applying the inverse wavelet transform (IWT) for each oversampled detailed image (fig. 2).

![Fig. 1 One-level DWT](image1)

![Fig. 2 subband HH of One-level DWT Resized at NxN](image2)

The features we use in this work are based on two statistics computed from the wavelet detail subbands. The coefficients of \( D_k^m \) will be denoted by \( d_k^m(i,j) \); \( 1 < i,j < N \) where \( k \) identifies the detail subband, \( i.e. k \in \{HL, LH\} \), in the level of decomposition. Note, that the dimensionality of the subbands (N) is equal to dimensionality of the input image.

The first feature we compute is called the mean deviation \( MD_k^m \), given by:

\[ MD_k^m = \frac{1}{N^2} \sum_{i=1}^{NW} \sum_{j=1}^{NW} \left| d_k^m(i,j) - \overline{d_k^m} \right| \]  

(1)

The second feature we employ is the standard deviation \( \sigma_k^m \) of the coefficients of a subband given by:

\[ \sigma_k^m = \left( \frac{1}{NW^2} \sum_{i=1}^{NW} \sum_{j=1}^{NW} (d_k^m(i,j) - \overline{d_k^m})^2 \right)^{1/2} \]  

(2)

Other features are computed with different Gabor filters for each pixel within the local window \( W \). After applying Gabor filters on the image with different orientation at different scale, the energy content \( E \), is calculated. The mean \( \mu \) and standard deviation \( \sigma \) of all transformed coefficients are computed, by using the following equations:

\[ E = \sum_{i=1}^{NW} \sum_{j=1}^{NW} |I(i,j)| \]

(3)

Where \( I(I,J) \) is the filtered image

\[ \mu = \frac{E}{NW \times NW} \]

(4)

To compute Gabor standard deviation features (\( \sigma \)), we used the same equation (Eq. (2)) as used for the wavelet features.
V. EXPERIMENTAL RESULTS

To evaluate the performance of this analyze we applied the methodology to a Brodatz database and to MSG images. Texture features extracted from Gabor filters and wavelet decomposition are used as inputs for the K-means clustering method, which results in a segmented image whose regions are distinct from each other with respect to texture characteristic content. Fig. 2 shows the segmented results.

For a wavelet decomposition of level up to level \(d\), this yields \(3d + 1\) features. One to two levels of decomposition appears reasonable for texture segmentation.

It is found that using the HH channel of each level of decomposition to provide features can degrade the classification performance, as these channels tend to contain the majority of noise in the image. Significant energy will be there in HL and LH channels of first level decomposition. For these reasons HH channel information is not used for
classification. It is useful to exploit the HL and LH channels coefficients to capture textural information with minimum increase in computations.

The Daubechies Daub4 wavelet decomposition gave the best result in this study (quadratic spline, Symlet, Coiflet and biorthogonal wavelets were also tested).

The feature vector we are using contains the mean deviation and the standard deviation of the modulus of LH and HL channels.

The energies, mean and standard deviation of the outputs of gabor filters are also computed. We employ a bank of gabor filters tuned at 8 different orientations $\Theta$ linearly varying from $0 < \Theta < \pi$, and at 5 different high-frequencies (per orientation), with an octave scale of spatial frequency, for multi-scale analysis. The filtered images are then grouped according to the orientation of the filters, thus resulting in 8 images ; one per orientation.

Experimental results on fused features demonstrated the combination of two feature sets always outperformed each method individually (ie: use of the gabor filtered or wavelet decomposition separately). The proposed feature extraction and classification scheme achieved high accuracies, with an overall classification accuracy of 96.47%.

VI. CONCLUSION

In this paper, we have presented an algorithm for texture segmentation based on multi-resolution filtering techniques. We investigated the texture classification problem with multi-resolution features, i.e., dyadic wavelet and Gabor filters. The Kmeans algorithm is used as classifiers. Texture segmentation results depict the novelty and significance of this method. Our method offers promising results. Experimental results on fused features demonstrated the combination of two feature sets always outperformed each method individually. Fused feature sets of multi-orientation decompositions, Gabor filters, and wavelet decomposition achieved the highest accuracies.

REFERENCES


