Wavelet Transform in Image Regions Classification

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Abstract

Texture segmentation and classification form very important topics of the interdisciplinary area of digital signal processing with many applications in different areas including analysis of microscopic images, biomedical image processing or detection of satellite image components. The paper presents selected mathematical tools for pattern recognition applied in crystalography to detect individual objects, to analyze their properties and to find the percentage of desired individuals. Proposed methods have been verified for simulated structures and then used for analysis of microscopic images of crystals of different shapes and sizes.

1. Introduction

A basic problem encountered in digital image processing is in image de-noising [1], restoration of their missing or corrupted components [2] and their enhancement [3], feature extraction [4] and classification [5].

The paper is devoted to image segmentation and to the application of discrete wavelet transform for image segments feature extraction using their boundary signals [6], [7]. Image components detection [8] and feature extraction can then be followed by classification using self-organizing neural networks [9]. The paper presents their use in this case estimating class boundaries as well.

An example of the application of proposed methods in crystallography is presented in Fig. 1(a) showing the microscopic image of crystals of different shapes, textures and sizes. Similar methods can be also used in other ares including biomedical imaging, environmental image processing or analysis of satellite observations.

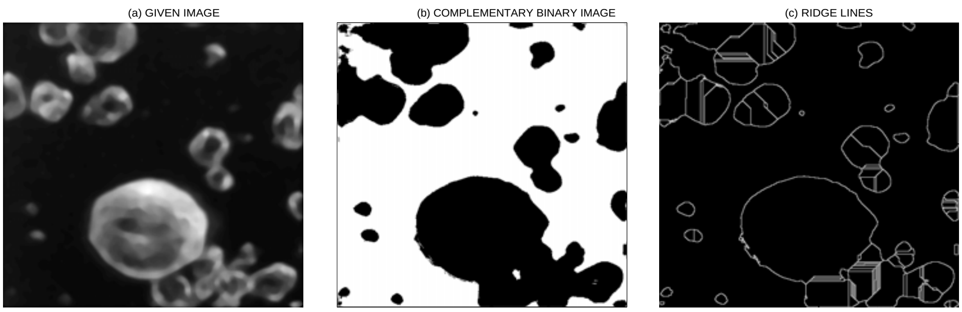

Fig. 1. Crystallographic image processing presenting **(a)** microscopic image, **(b)** its binary representation, and **(c)** ridge lines detection resulting from its watershed transform

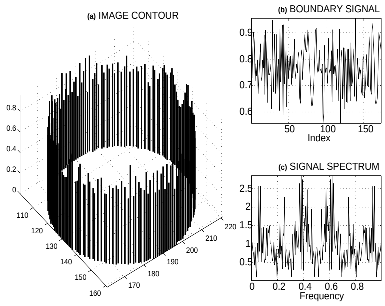

Fig. 2. Selected image segment analysis showing **(a)** its boundary signal in three dimensions, **(b)** the boundary signal in two dimensions, and **(c)** its discrete Fourier transform

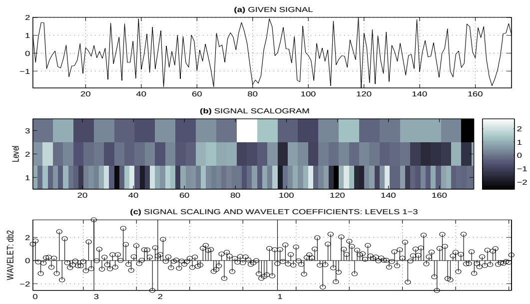

Fig. 3. Selected image segment analysis presenting **(a)** two dimensional image segment boundary signal, **(b)** scalogram presenting coefficients of its decomposition into three levels, and **(c)** wavelet transform coefficients organized in a row vector

2. Image Segmentation

Segmentation represents an important initial step of image processing. Figs 1(b),(c) present an example of a such a process for image components of different shapes and textures and their segmentation using the watershed method [5]. The proposed algorithm consists of these steps

- image thresholding to convert it to the black and white form
- distance and watershed transform use to find image ridge lines presented in Fig. 1(b)
- ridge lines detection presented in Fig. 1(c)

The process of classification assumes definition of a pattern matrix containing features of separate image segments. Many possibilities of their extraction [4] include

- analysis of statistical properties of the boundary signal (see Fig. 2(a)) or segment structure in the space domain
- transform of boundary signal or segment structure allowing feature specification in the transform domain using discrete Fourier transform or discrete wavelet transform among others

The boundary signal of a segment in Figs 2(a),(b) in three or two dimensions and its discrete Fourier transform are shown in Fig. 2(c). Image features used for classification can be based upon the mean value and the variance of discrete Fourier transform coefficients. Wavelet transform discussed further can be even more efficient allowing multiresolution signal or image analysis.

3. Image Wavelet Decomposition and Reconstruction

Signal wavelet decomposition using Discrete Wavelet Transform (DWT) provides an alternative to the Discrete Fourier Transform (DFT) for signal analysis resulting in signal decomposition into two-dimensional functions of time and scale. The main benefit of DWT over DFT is in its multi-resolution time-scale analysis ability according to Fig.5.

The principle of signal and image wavelet decomposition and reconstruction [10], [3] is presented in Fig. 4 for an image matrix $[g(n,m)]_{N,M}$ or one-dimensional signal $x[n]_{N,1} = [g(n,1)]_{N,1}$ considered as a special case of an image having one column only.

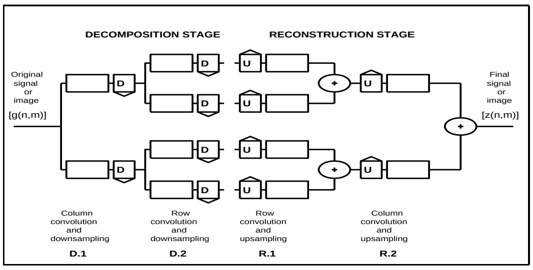

Fig. 4. Wavelet transform use in image decomposition and reconstruction

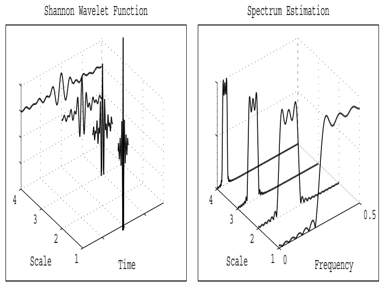

Fig. 5. Shannon wavelet and the effect of its dilation to spectrum compression

The high-pass filter and the complementary low-pass filter is applied to image columns and then to its rows followed by downsampling after each processing stage. Resulting coefficients can be used for image or signal analysis or for its reconstruction again. Fig. 3 presents wavelet decomposition of a selected image segment boundary signal.

Studying the first decomposition step let us denote a column of the image matrix $[g(n,m)]_{N,M}$ as signal $\{x(n)\}_{n=0}^{N-1} = [x(0), x(1), ..., x(N-1)]'$. This signal can be analyzed by half-band low-pass and high-pass filters with their impulse responses

$$\{s(n)\}_{n=0}^{L-1} = [s(0), s(1), \cdots, s(L-1)], \quad \{w(n)\}_{n=0}^{L-1} = [w(0), w(1), \cdots, w(L-1)] \quad (1)$$

The first stage (see Fig. 4) assumes the convolution of a given signal and the appropriate filter for decomposition of all image columns at first at first by relations

$$xl(n) = \sum_{k=0}^{L-1} s(k)x(n-k), \quad xh(n) = \sum_{k=0}^{L-1} w(k)x(n-k) \quad (2)$$

for all values of n followed by subsampling by factor $c = 2$. In the following decomposition stage $D.2$, the same process is applied to rows followed by row downsampling to form four separate images. The low-low subimage can be further decomposed and results used for image reconstruction again. In the case of one-dimensional signal processing, steps $D.2$ and $R.1$ are omitted. The whole process can be used for signal or image

1) decomposition and perfect reconstruction allowing signal compression and de-noising
2) resolution enhancement and interpolation
3) feature extraction using the variance of summed squared coefficients

In all these cases the multiresolution properties of wavelet transform are used.

4. Image Regions Classification

Classification of Q segments using R features organized in pattern matrix $\mathbf{P}_{R,Q}$ can be realized by application of self-organizing neural networks. The number S of output layer elements is equal to image classes and must be either defined in advance or it can be automatically increased to create new classes. During the learning process network weights forming matrix $\mathbf{W}_{S,R}$ are changed to minimize distances between each input vector and corresponding weights of a winning neuron characterized by its coefficients closest to the current pattern. In case that the learning process is successfully completed network weights belonging to separate output elements represent typical class individuals.

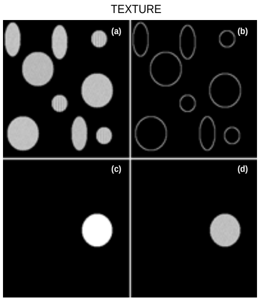

Fig. 6. Results of simulated texture segmentation

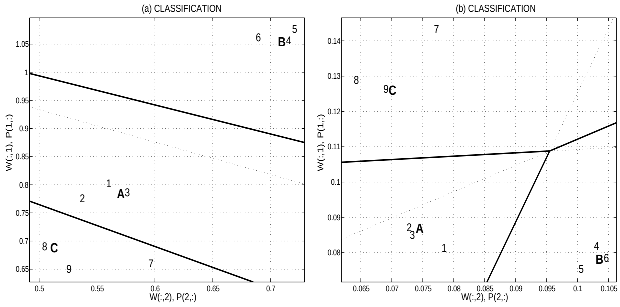

Fig. 7. Results of **(a)** the discrete Fourier transform, and **(b)** the discrete wavelet transform for the simulated image classification into three classes

Class boundaries presented in Fig. 7 are defined by values of matrix $\mathbf{W}_{S,R}$ and for $R = 2$ have been evaluated by a special algorithm dividing the plane into the number of regions equal to classes.

Results of classification of 9 image segments given in Fig. 6(a) into three classes are presented in Fig. 7 for two selected signal features obtained (i) as the mean and variance of discrete Fourier transform (DFT) coefficients and (ii) by the variance of discrete wavelet transform (DWT) coefficients at the first and the second decomposition level. Location of features is given by position of segment numbers. Results obtained by both methods are the same but the variance of features evaluated by the DWT is smaller comparing to that obtained by the DFT.

5. Results

The method presented has been applied for several kinds if real images. Results of processing of the real biomedical MR image are presented in Fig. 8. Image segmentation using watershed transform is able to detect most of image segments even though the problem of fault class boundaries can arise in some cases.

The results of classification of Q image segments with feature matrix $\mathbf{P}_{R,Q} = [\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_Q]$ for the selection of different sets of $R = 2$ features and C classes have

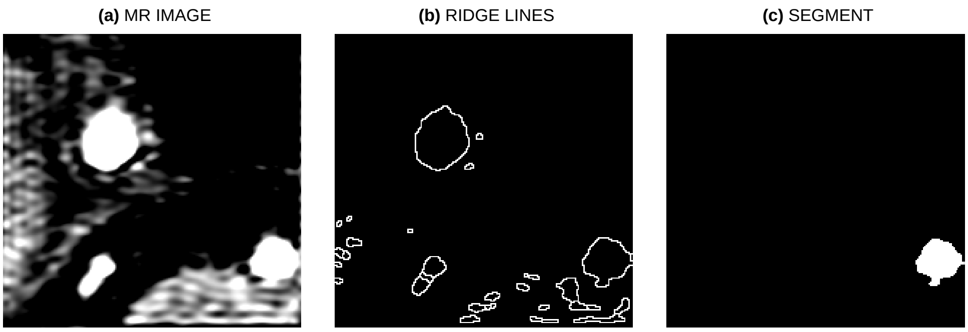

Fig. 8. An example of MR image segmentation presenting **(a)** original MR area, **(b)** ridge lines resulting from its watershed segmentation, and **(c)** a selected segment standing for a vein

been numerically compared by the proposed criteria function. Each class $i = 1, 2, \cdots, C$ can be characterized by the mean distance of column feature vectors $\mathbf{p}_{j_k}$ belonging to class segments j_k for $k = 1, 2, \cdots, N_i$ from the class centre in the $i-$th row of matrix $\mathbf{W}_{C,R} = [\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_C]'$ by relation

$$ClassDist(i) = \frac{1}{N_i} \sum_{k=1}^{N_i} dist(\mathbf{p}_{j_k}, \mathbf{w}_i) \quad (3)$$

where N_i represents the number of segments belonging to class i and function $dist$ is used for evaluation of the Euclidean distance between two vectors. Results of classification can be numerically characterized by the mean value of average class distances related to the mean value of class centers distances obtained after the learning process according to relation

$$crit = mean(ClassDist)/mean(dist(\mathbf{W}, \mathbf{W}')) \quad (4)$$

This proposed Cluster Segmentation Criterion (CSC) provides low values for compact and well separated clusters while close clusters with extensive dispersion of cluster vectors provide high values of this criterion.

6. Conclusion

The paper presents some aspects of image components classification using wavelet transform which provides many possibilities of detection of image segment features owing to its multiresolution properties. Segments boundary signals were used for image classification even though there is possible to use two dimensional wavelet transform for detection of patterns of individual segments texture, too.

Methods discussed in the paper have been applied to shape analysis of microscopic images of crystals. Similar methods can be used in other applications in a wide range of interdisciplinary problems of texture analysis including biomedical imaging, processing of satellite images, communications and remote earth observations.

Acknowledgments

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References

[1] Saeed V. Vaseghi, *Advanced Digital Signal Processing and Noise Reduction*, Wiley & Teubner, West Sussex, U.K., second edition, 2000.

[2] Onur G. Guleryuz, "Iterated Denoising for Image Recovery," in *Data Compression Conference (DCC '02), Snao Bird, Utah*. 2002, IEEE.

[3] J. Ptáček, I. Šindelářová, A. Procházka, and J. Smith, "Wavelet Transforms In Signal And Image Resolution Enhancement," in *International Conference Algoritmy 2002, Podbanske*. 2002, STU.

[4] M. Nixon and A. Aguado, *Feature Extraction & Image Processing*, NewNes Elsevier, 2004.

[5] R. C. Gonzales, R. E. Woods, and S. L. Eddins, *Digital Image Processing Using MATLAB*, Prentice Hall, 2004.

[6] S. Arivazhagan and L. Ganesan, "Texture Classification Using Wavelet Transform," *Pattern Recogn. Lett.*, vol. 24, no. 9-10, pp. 1513–1521, 2003.

[7] S. Li and J. Shawe-Taylor, "Comparison and fusion of multiresolution features for texture classification," *Pattern Recogn. Lett.*, vol. 25, 2004.

[8] T. Randen and J. H. Husoy, "Filtering for Texture Classification: A Comparative Study," *IEEE Trans. on PAMI*, vol. 21, no. 4, pp. 291–310, 2000.

[9] C. M. Bishop, *Neural Networks for Pattern Recognition*, Oxford University Press, 1995.

[10] N. G. Kingsbury, "Complex Wavelets for Shift Invariant Analysis and Filtering of Signals," *Journal of Applied and Computational Harmonic Analysis*, vol. 10, no. 3, pp. 234–253, May 2001.