WAVELET USE FOR IMAGE CLASSIFICATION

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Abstract: The paper presents selected mathematical methods of image analysis including their segmentation, thresholding and feature extraction to detect specific image regions and to find their properties. The main part of the paper presents possibilities of the application of wavelet transform to find segment features using both their boundary signals and image components textures. Resulting features are then used for image segments classification by self-organizing neural networks. Proposed methods are verified for simulated image components of various sizes, rotations and textures in the Matlab environment and then used for analysis of microscopic crystal shapes and structures.

Keywords: Image segmentation, distance transform, watershed transform, image features, wavelet transform, neural network classification, computational intelligence

1. INTRODUCTION

Segmentation of image components, their features extraction and classification represent a specific interdisciplinary area of image processing studied in many papers and books including studies of C. et al. (2004) or M. and Aguado (2004).

The main part of the paper presents the use of wavelet transform (I., 1990; E., 1994) for image features extraction using decomposition of image segments boundary signals or their pattern recognition. Selected features are then used for image segments classification using self-organizing neural networks (S., 1994; M., 1994). The paper presents a specific method for visualization of class boundaries based upon the work of A. and Štorek (1995).

All methods are verified for simulated images of different textures and sizes in the Matlab environment and then used for classification of the microscopic view of crystal shapes and their patterns presented in Fig. 1. Similar approach can be used for analysis of other structures including biomedical images as well.

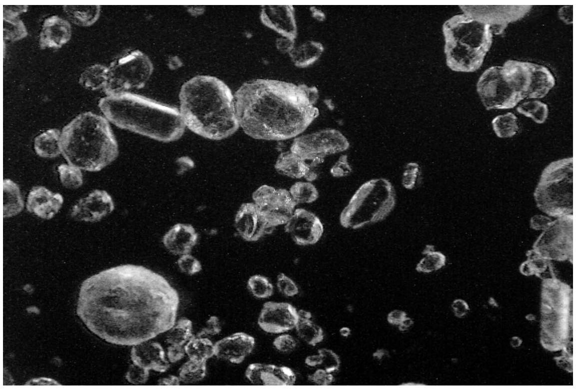

Fig. 1. Microscopic image of crystals of different shapes, textures and sizes

2. WAVELET TRANSFORM AND IMAGE DECOMPOSITION

Wavelet decomposition using the 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 the DWT over the DFT is in its multi-resolution time-scale analysis ability.

Wavelet functions used for signal analysis are derived from the initial function $W(t)$ forming basis for the set of functions

$$W_{m,k}(t) = \frac{1}{\sqrt{a}}\, W\,(\frac{1}{a}\,(t-b)) \qquad (1)$$

for discrete parameters of dilation $a = 2^m$ and translation $b = k\;2^m$. Wavelet dilation, which is closely related to spectrum compression, enables local and global signal analysis. This decomposition can be used for signal de-noising studied by A. and Procházka (2004) or image processing studied by G. and Magarey. (1997) or A. et al. (2005).

In the case of the following studies the decomposition of one-dimensional and two-dimensional data is used for features extraction using the Mallat's decomposition scheme based upon convolution of signal values with wavelet decomposition coefficients studied by J. et al. (2002). Statistical properties of resulting wavelet transform coefficients are then used for extraction of signal or image features.

3. IMAGE COMPONENTS SEGMENTATION

Image segmentation represents an important initial step of image processing. Fig. 2(a) presents an example of a simulated image containing segments of different shapes and textures and segments extraction using the watershed method described by C. et al. (2004). The proposed algorithm consists of these steps

(1) Conversion of the given image to its binary form using a selected threshold level
(2) Distance transform application to the binary image
(3) Watershed transform use to find ridge lines separating image components

These three steps are presented in Fig. 2 for a simulated image processing.

3.1 *Distance transform*

The distance transform represents a mathematical tool used in conjunction with the watershed transform and its application for image segmentation

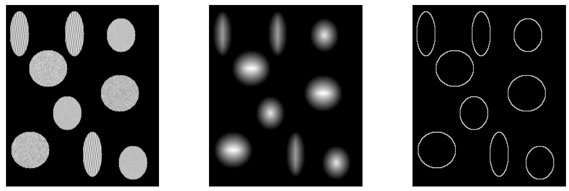

Fig. 2. Image segmentation presenting **(a)** an image containing different simulated structures, **(b)** results of the distance transform, and **(c)** results of the watershed transform and ridge lines separating individual images

(C. et al., 2004). For a two dimensional image it computes the Euclidean distance transform of the binary image. As a result it assigns to each pixel in the binary image the distance between the actual pixel and the nearest nonzero image pixel. Evaluated values of this process are presented in Fig. 2(b) in the grey scale with white pixels in locations having the largest distance from the nonzero image values.

3.2 *Watershed transform*

A watershed transform is based upon the geographical meaning of this word defining a ridge of high land separating river system and dividing the country into areas drained by different rivers. A catchment basin means in this sense an area from which rainfall flows into a river or reservoir.

The watershed transform applies these ideas to the gray-scale image processing in a way that can be used to solve a variety of image segmentation problems. The watershed transform finds the catchment basins and ridge lines in a gray-scale image. In terms of the problem related to image segmentation the key concept is to change the starting image into another one whose catchment basins are the objects or regions we want to identify as studied by C. et al. (2004) for instance.

Image transform using the watershed method should be applied to a matrix after its proper pre-processing to obtain the best image objects contours. In the case of a simulated image presented in Fig. 2 all zero pixels of the complementary image have been assigned by $-\infty$ at first. The matrix processed by the watershed transform in the next step resulted in a labelled matrix identifying the watershed regions with its integer elements greater than or equal to 0. Its zero values identify image contours and nonzero elements belong to watershed regions. The final operation consists of the assignment of values 1 to zero elements and values 0 to all nonzero elements with results presented in Fig. 2 (c).

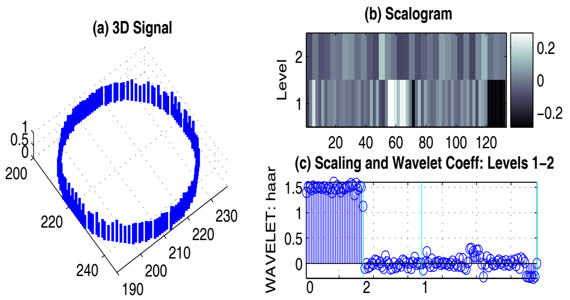

Fig. 3. Analysis of a selected image component contour signal presenting **(a)** contour signal in 3D , **(b)** its scalogram, and **(c)** scaling and wavelet coefficients after the contour signal decomposition

4. FEATURE EXTRACTION

After image segmentation it is possible to extract individual image components and for each of them to find both its image contour signal and image texture matrix as objects for their features extraction. Each signal and matrix can be analysed both by the discrete Fourier transform and discrete wavelet transform. An example of the application of the DWT to image contour signal is presented in Fig. 3 together with scalogram of wavelet coefficients decomposition into the second level. Fig. 4 presents similar process of the two dimensional DWT decomposition applied to a selected image segment.

The image classification assumes definition of a pattern matrix containing features obtained from image object signals or textures. Features obtained are based upon the mean value and the variance of

(1) image segments contour signals and their texture
(2) coefficients obtained after the discrete Fourier transform application to contour signals and segments textures

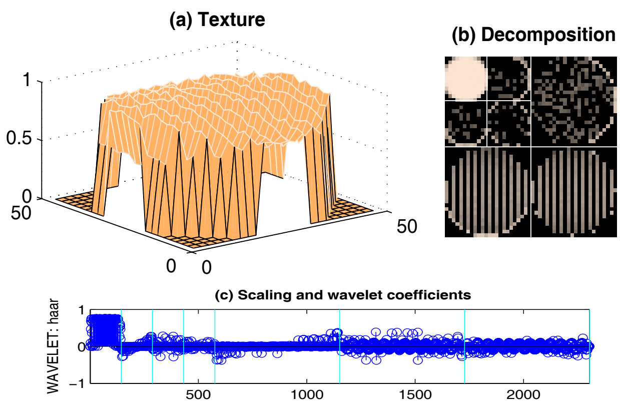

Fig. 4. Analysis of selected image component presenting **(a)** its texture in 3D , **(b)** its decomposition to the second level, and **(c)** scaling and wavelet coefficients after decomposition

(3) wavelet coefficients evaluated after the discrete wavelet transform application both to contour signals and segments textures

Having Q image objects it is possible to define pattern matrices $P_{F,Q}$ in this way using F features. These pattern matrices represent inputs into a self-organizing neural network.

5. IMAGE COMPONENTS CLASSIFICATION

Self-organizing networks form one of the most fascinating topics in the neural network field. Such networks can learn to detect regularities and correlations in their input vectors and they can adapt their coefficients to recognize groups of similar input vectors (A. et al., 2004).

The process of feature extraction described above results in the definition of the pattern matrix values forming inputs into a self-organizing neural network in each its column. The following classification has been used for three images in this study representing

(1) simulated image presented in Fig. 5 (a)
(2) modified image in Fig. 5 (b) with rotated objects in the image
(3) image in Fig. 5 (c) with image objects of different sizes

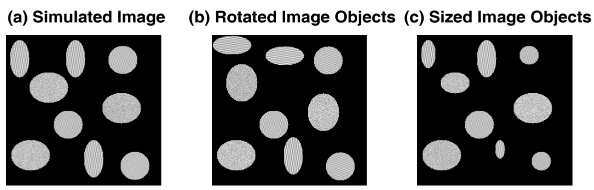

Fig. 5. Modification of images presenting **(a)** a standard image, **(b)** image with rotated objects, and **(c)** image objects of different sizes

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 by special methods. During the learning process network weights forming matrix $W_{S,F}$ 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 the case that the learning process is successfully completed network weights belonging to separate output elements represent typical class individuals A. et al. (2005).

Results of classification of simulated images in Fig. 5 (a) are presented in Fig. 6. The first pair of pictures present the process of classification of features evaluated from boundary signals but the results are not correct as the division of image components into 3 classes is not right. On

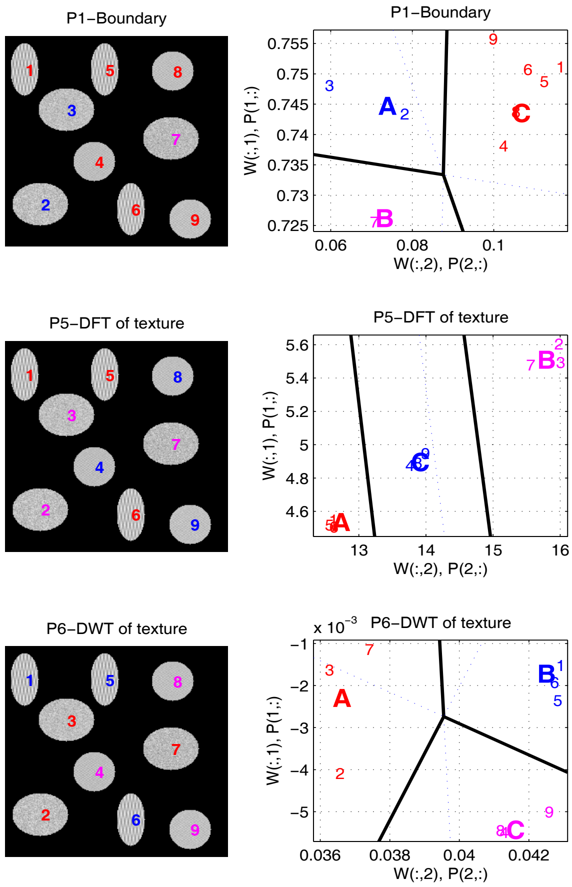

Fig. 6. Classification of simulated images presenting in the first column simulated images with numbered image components using the same colors as that used for the corresponding image classes presented in the second column together with individual class boundaries

the contrary to this classification it is possible to obtain excellent results of classification using features evaluated from coefficients of Fourier and wavelet transforms as displayed in further two pairs of pictures in Fig. 6.

Each image is classified separately and results of classification are summarized in tables described further.

6. RESULTS

Tables 1, 2 and 3 summarize complete results of classifications of simulated images displayed in Fig. 5. They compare image segments classification into three classes using two features evaluated from the mean value and variance obtained by methods introduced in Section 3.

Dark columns indicate, from which features, obtained by existing ways, there was the classification process successful. Comparison of results between 2D-DFT and 2D-DWT presented in Tab. 1 show the efficiency of the wavelet transform as the standard deviation achieved is the smallest of all successful classifications.

Classification of simple image							
		Boundary features			Texture features		
		No transform	*DFT*	*DWT*	*No transform*	*2DFT*	*2DWT*
A	*length*	1	3	1	2	3	3
	typical element	3	6	2	1	1	2
	standard deviation	0.0000	0.0215	0.0000	0.0015	0.0329	0.0005
B	*length*	6	3	3	6	3	3
	typical element	6	7	5	4	2	4
	standard deviation	0.0044	0.0201	0.0016	0.0036	0.1564	0.0002
C	*length*	2	3	5	1	3	3
	typical element	7	9	8	7	8	6
	standard deviation	0.0046	0.0151	0.0024	0.0000	0.0250	0.0004

Table 1. Comparison of simple image segments classification into 3 classes

7. CONCLUSION

The paper presents possibilities of image classification starting from image components segmentation, feature extraction and their classification by self-organizing neural networks. The main result of the study is in the comparison of image feature extraction using discrete wavelet transform with that obtained by the discrete Fourier transform and presenting the efficiency of discrete wavelet transform decomposition.

Further result of the study is in the comparison of image objects feature extraction using their boundary signals and their texture analysis.

Classification of rotated image							
		Boundary features			Texture features		
		No transform	*DFT*	*DWT*	*No transform*	*2DFT*	*2DWT*
A	*length*	1	3	4	1	5	3
	typical element	3	4	2	3	1	1
	standard deviation	0.0000	0.0262	0.0016	0.0000	0.1567	0.0010
B	*length*	2	3	2	6	1	2
	typical element	7	5	3	4	4	2
	standard deviation	0.0042	0.0380	0.0029	0.0014	0.0000	0.0011
C	*length*	6	3	3	2	3	4
	typical element	9	7	5	7	7	8
	standard deviation	0.0032	0.0110	0.0054	0.0004	0.2470	0.0012

Table 2. Comparison of rotated segments image classification into 3 classes

Classification of sized image							
		Boundary features			**Texture features**		
		No transform	*DFT*	*DWT*	*No transform*	*2DFT*	*2DWT*
A	*length*	**3**	4	3	2	2	5
	typical element	**3**	4	2	2	2	5
	standard deviation	**0.0033**	0.0411	0.0011	0.0006	0.0737	0.0011
B	*length*	**3**	3	3	5	3	1
	typical element	**5**	7	6	4	5	6
	standard deviation	**0.0026**	0.0281	0.0031	0.0041	0.6952	0.0000
C	*length*	**3**	2	3	2	4	3
	typical element	**9**	9	8	6	9	8
	standard deviation	**0.0018**	0.0077	0.0006	0.0006	1.2026	0.0014

Table 3. Comparison of classification of image segments of different sizes into 3 classes

It is assumed that further studies will be devoted to different methods of image segmentations and to wavelet transform analysis. In this connection there will be studied different wavelet functions to obtain the most reliable features with their class variance as small as possible.

Selected applications will be devoted both to real and microscopic image processing representing crystal structures and biomedical magnetic resonance images.

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References

Gavlasová A. and A. Procházka. Wavelet Transformace v potlačování rušivých složek obrazů. *In Konference MATLAB 2004, Praha*, 2004.

Procházka A., A. Gavlasová, and K. Volka. Wavelet Transform in Image Recognition. *International Symposium ELMAR-2005*, April 2005.

Procházka A., V. Musoko, and M. Kolínová. Image Classification Using Self-Organizing Neural Networks. *In Konference MATLAB 2004, Praha*, 2004.

Procházka A. and M. Štorek. Wavelet Transform Use for Signal Classification by Self-Organizing Neural Networks. In *Fourth International Conference on Artificila Neural Networks ANN-97*. IEE, Cambridge, England, 1995.

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

Newland D. E. *An Introduction to Random Vibrations, Spectral and Wavelet Analysis*. Longman Scientific & Technical, Essex, U.K., third edition, 1994.

Kingsbury N. G. and J. F. Magarey. Wavelet Transforms in Image Processing. *Proc. First European Conference on Signal Analysis and Prediction*, 1997.

Daubechies I. The Wavelet Transform, Time-Frequency Localization and Signal Analysis. *IEEE Trans. Inform. Theory*, 36:961–1005, September 1990.

Ptáček J., I. Šindelářová, A. Procházka, and J. Smith. Wavelet Transforms In Signal And Image Resolution Enhancement. In *International Conference Algoritmy 2002, Podbanske*. The Slovak Technical University, 2002.

Bishop C. M. *Neural Networks for Pattern Recognition*. Oxford University Press, Oxford, 1994.

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

Haykin S. *Neural Networks*. IEEE Press, New York, 1994.