Wavelet Transform in Biomedical Image Segmentation and Classification

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Abstract

Segmentation, feature extraction and classification stand for important topics of biomedical image processing with further use in microscopy and cell analysis. The paper presents the use of wavelet transform for signal or image decomposition and reconstruction allowing time scale signal analysis, image de-noising, resolution changes and feature extraction. The main part of the paper is devoted to image regions boundary detection and wavelet decomposition of resulting boundary signals to find features for the following segments classification. Results of classification achieved by self-organizing neural networks using features obtained by the discrete wavelet transform are compared with that obtained by the discrete Fourier transform. Proposed algorithms have been verified for simulated structures and then used for analysis of biomedical magnetic resonance images of the brain slice.

Key words: Digital Image Processing, Time Scale Signal Analysis, Wavelet Transform, Resolution Enhancement, Texture Analysis, Contour Detection, Signal De-Noising, Thresholding, Segmentation, Feature Extraction, Classification, Artificial Neural Networks, Biomedical Image Processing

1 Introduction

A fundamental problem encountered in the digital processing of both one-dimensional and multi-dimensional signals is the selection of the signal resolution. This defines the sampling period in the case of time series or the pixel distance in the case of images. Signal and image resolution enhancement is therefore one of basic problems in signal analysis.

Further problems of digital image processing studied by Newland (1994), Nixon and Aguado (2004), Vaseghi (2000) or Gonzales et al. (2004) include

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image de-noising, feature extraction and classification. Restoration of missing or corrupted components of images studied e.g. by Guleryuz (2002) or Duci et al. (2002) belong to further important topics of research.

The paper is devoted to the use of wavelet transform and multi-resolution image decomposition allowing image components detection (Arivazhagan and Ganesan, 2003, 2004; Randen and Husoy, 2000; Li and Shawe-Taylor, 2004), segmentation and feature extraction for their classification. The paper presents a proposed method using self-organizing neural networks presented e.g. by Bishop (1995) and class boundary estimation.

An example of proposed methods in biomedicine presented in Fig. 1 shows (a) the magnetic resonance image of the brain region and (b) the same image after its wavelet resolution enhancement presented e.g. by Ptáček et al. (2002). Specific topics of the use of wavelet functions in magnetic resonance imaging have been studied e.g. by Breakspear et al. (2004), Bullmore et al. (2004) or Bullmore et al. (2003).

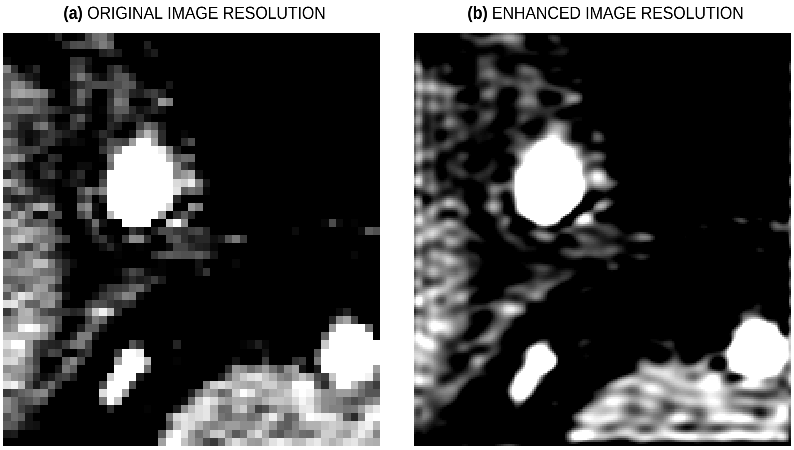

Fig. 1. Magnetic resonance image of the brain region presenting **(a)** original image and **(b)** result of its resolution enhancement by wavelet transform

2 Signal Wavelet Decomposition

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

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

$$h_{m,k}(t) = \frac{1}{\sqrt{a}}\, h\,(\frac{1}{a}\,(t-b)) = \frac{1}{\sqrt{2^m}}\, W\,(2^{-m}t-k) \qquad (1)$$

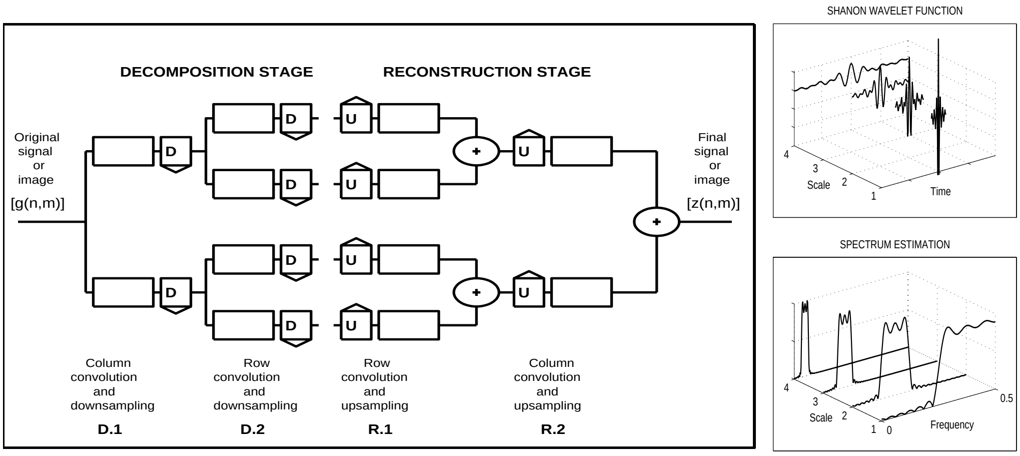

Fig. 2. Wavelet transform use in signal decomposition and the effect of Shannon wavelet function dilation to its spectrum compression

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.

The principle of signal and image decomposition and reconstruction for resolution enhancement is presented in Fig. 2 for an image matrix $[g(n,m)]_{N,M}$ or a one-dimensional signal considered as a special case of an image having one column only.

The decomposition stage includes the processing of the image matrix by columns at first using wavelet (high-pass) and scaling (low-pass) function followed by row downsampling by factor D in stage $D.1$. To study this problem let us denote a selected column of the image matrix $[g(n,m)]_{N,M}$ as signal $\{x(n)\}_{n=0}^{N-1} = [x(0), x(1), ..., x(N-1)]^T$. This signal can be analyzed by a half-band low-pass filter with its impulse response

$$\{s(n)\}_{n=0}^{L-1} = [s(0), s(1), \cdots, s(L-1)] \tag{2}$$

and complementary high-pass filter having impulse response

$$\{w(n)\}_{n=0}^{L-1} = [w(0), w(1), \cdots, w(L-1)] \tag{3}$$

The first stage assumes the convolution of a given signal and the appropriate filter for decomposition at first by relations

$$xl(n) = \sum_{k=0}^{L-1} s(k)x(n-k) \qquad\qquad xh(n) = \sum_{k=0}^{L-1} w(k)x(n-k) \tag{4}$$

for all values of n followed by subsampling by factor D. In the following decomposition stage $D.2$ the same process is applied to rows of the image matrix followed by row downsampling. The decomposition stage results in this way in four images representing all combinations of low-pass and high-pass initial image matrix processing.

The *reconstruction stage* includes row upsampling by factor U at first and row convolution in stage $R.1$. The corresponding images are then summed. The final step $R.2$ assumes column upsampling and convolution with reconstruction filters followed by summation of the results again. In the case of one-dimensional signal processing, steps $D.2$ and $R.1$ are omitted.

The whole process of signal or image wavelet decomposition and reconstruction can be used for signal or image

(1) decomposition and perfect reconstruction allowing signal or image analysis and compression as studied by Kingsbury (2001) assumming downsampling D=2 and upsampling U=2
(2) resolution enhancement presented e.g. by Ptáček et al. (2002) assumming downsampling $D = 1$ and upsampling $U = 2$ with results presented in Fig. 1(b)
(3) de-noising based upon modification of signal/image decomposition coefficients by selected threshold limits studied into details by Kingsbury (2001)
(4) interpolation for reconstruction of corrupted image regions presented e.g. by A. Procházka and J. Ptáček (2004) and based upon iterative image de-noising
(5) feature extraction using e.g. the variance of coefficients at a selected level of decomposition studied by Nixon and Aguado (2004)

In all these cases the multi-resolution properties of wavelet transform are used. Fig. 2 presents this property for a Shannon wavelet function. Complex wavelets studied e.g. by Kingsbury (2001) provide much better results in many cases.

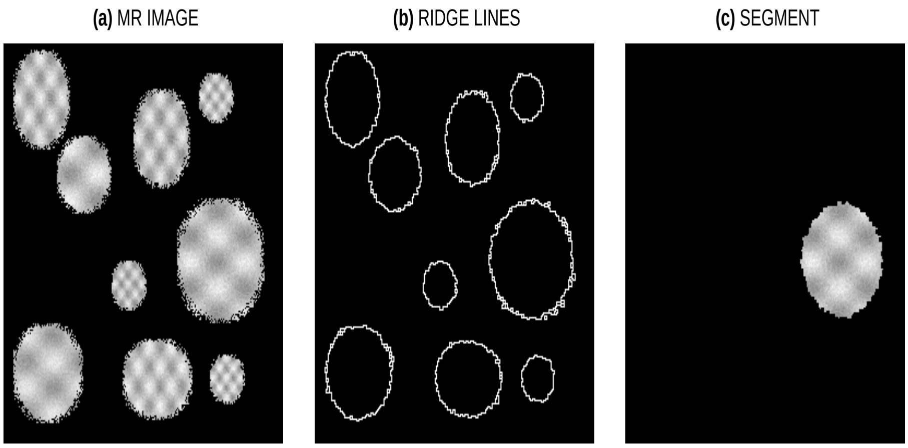

Fig. 3. Image segmentation presenting **(a)** an image containing different simulated structures, **(b)** results of its watershed segmentation, and **(c)** selected image segment area

3 Image Features Detection

A very common problem related to image regions classification is in image components contour detection. Fig. 3(a) presents an example of a simulated image containing segments of different shapes, volumes, rotations and textures and separate segments extraction using the watershed method presented by Gonzales et al. (2004). The proposed algorithm consists of these steps

- image thresholding for conversion to black/white form
- distance and watershed transform use to find image ridge lines presented in Fig. 3(b)
- extraction of a segment and its boundary (Fig. 3(c))

Principle of image segmentation and boundary signal definition is presented in Fig. 4. The following classification process assumes definition of a pattern matrix containing features of separate image segments. Many possibilities of their extraction (Nixon and Aguado, 2004) include analysis of

- image boundary signal or the texture inside its area
- statistical properties of boundary signal or segment structure
- transform of boundary signal or segment structure allowing its translation independence using discrete Fourier transform or discrete wavelet transform among others

Image features can be based upon the mean value and the variance of discrete Fourier transform coefficients. Wavelet transform can be even more flexible allowing multi-resolution signal or image analysis. Fig. 5 presents its applica-

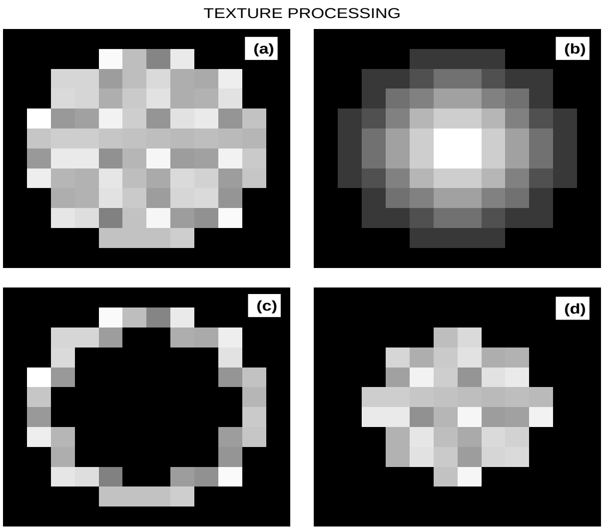

Fig. 4. Principle of image segmentation and image boundary selection presenting **(a)** selected image, **(b)** results of the distance transform of its black and white form, **(c)** its boundary values, and **(d)** its inner area pixels

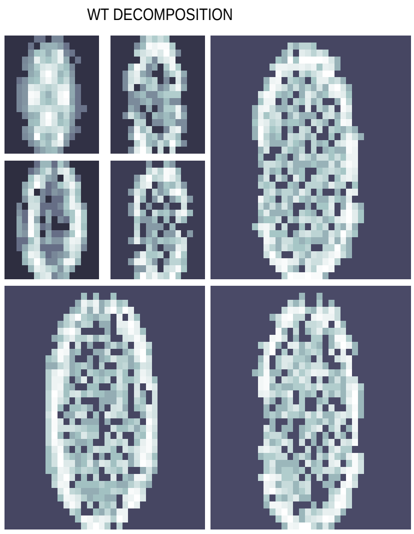

Fig. 5. Decomposition of the selected subimage using wavelet transform into the second level by Daubechies wavelet functions of the second order

tion to the image texture decomposition into the second level using Daubechies wavelet function while Fig. 6 shows the use of wavelet transform to boundary signal analysis applied for image segment selected in Fig. 3(c) in both cases. Further problems including rotation-invariant texture analysis are studied e.g. by Jafari-Khouzani and Zadeh (2005).

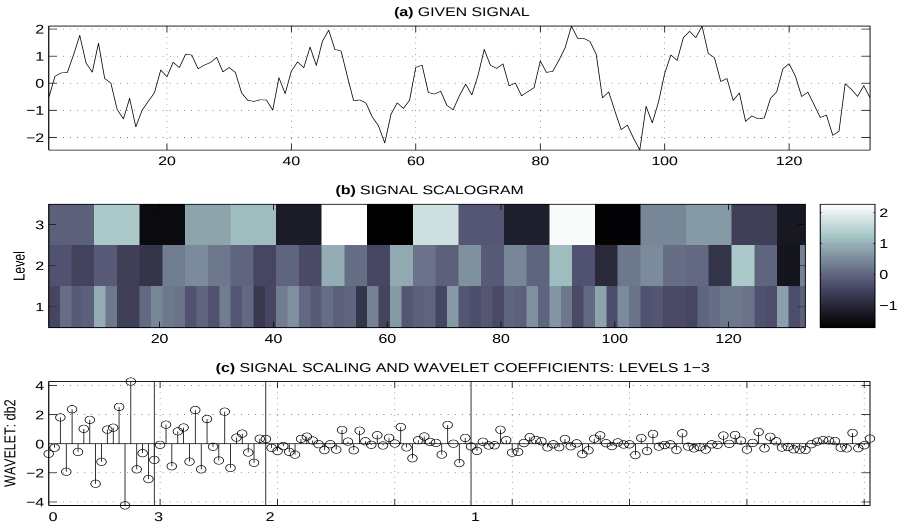

Fig. 6. Image segment analysis presenting **(a)** two dimensional image segment boundary signal, **(b)** scalogram of coefficients of its decomposition into three levels using Daubechies wavelet functions of the second order, and **(c)** wavelet transform coefficients organized in a row vector

4 Image Segments Classification

Classification of image segments using features forming a pattern matrix can be achieved by various methods of clustering analysis or by self-organizing neural networks. An example of signal features using boundary signals of simulated structures given above is presented in Fig. 7. In the case of neural networks the number of output layer elements is equal to image segment classes and their weight coefficients point to typical class features at the end of the learning process.

The classification method has been verified for image segments presented in Fig. 3(a) with randomly added texture component and randomly modified image shape boundaries. Results of classification into three classes are given 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 DB2 wavelet transform (DWT) coefficients at the first and the second decomposition level. For each class it is possible to find typical image element having the lowest Euclidian distance of its feature values and corresponding neuron coefficients and the variance of image features belonging to an individual class.

Table 1
COMPARISON OF IMAGE SEGMENTS CLASSIFICATION INTO THREE CLASSES USING TWO FEATURES EVALUATED BY DFT AND DWT USING THE DECOMPOSITION INTO THE THIRD LEVEL AND DAUBECHIES WAVELET FUNCTIONS APPLIED TO IMAGE SEGMENTS BOUNDARY SIGNALS

Feature	*Typical Class Image*		
	Class Mean Square Errors		
	A	*B*	*C*
DFT	2 0.003	4 0.006	9 0.012
DWT	3 0.002	6 0.001	8 0.007

Both DFT and DWT methods used for image featues extraction classify individual patterns into the same classes in this example but the variance of features related to the typical class element evaluated by the DWT is smaller comparing to that obtained by the DFT as presented in Table 1.

5 Results

The proposed methods of image segmentation have been applied to selected MR images. Numerical experiments proved the importance of a proper choice of the threshold limit to avoid oversegmentation that can cause serious problems in real image processing. To reduce this effect image de-noising can be applied in the image preprocessing stage. An example of real MR image seg-

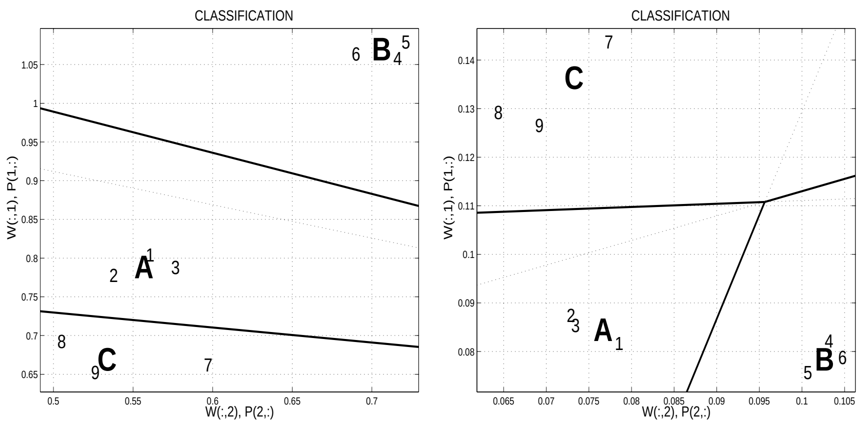

Fig. 7. The topography of features resulting from **(a)** the discrete Fourier transform and **(b)** the discrete wavelet transform for the simulated image and their classification into three classes providing class boundaries as well

mentation and analysis is presented in Fig. 8. A MR image (a) is thresholded and processed by the watershed transform (b) allowing the extraction of separate image component (c) representing a vain in this case. Image component boundary signal presented in (d) and (e) is then processed either by the discrete Fourier transform (f) of wavelet transform (g). Selected statistical properties of transform coefficients are subsequently used as image features. Such image features obtained for all image components are then stored in the pattern matrix used for their classification.

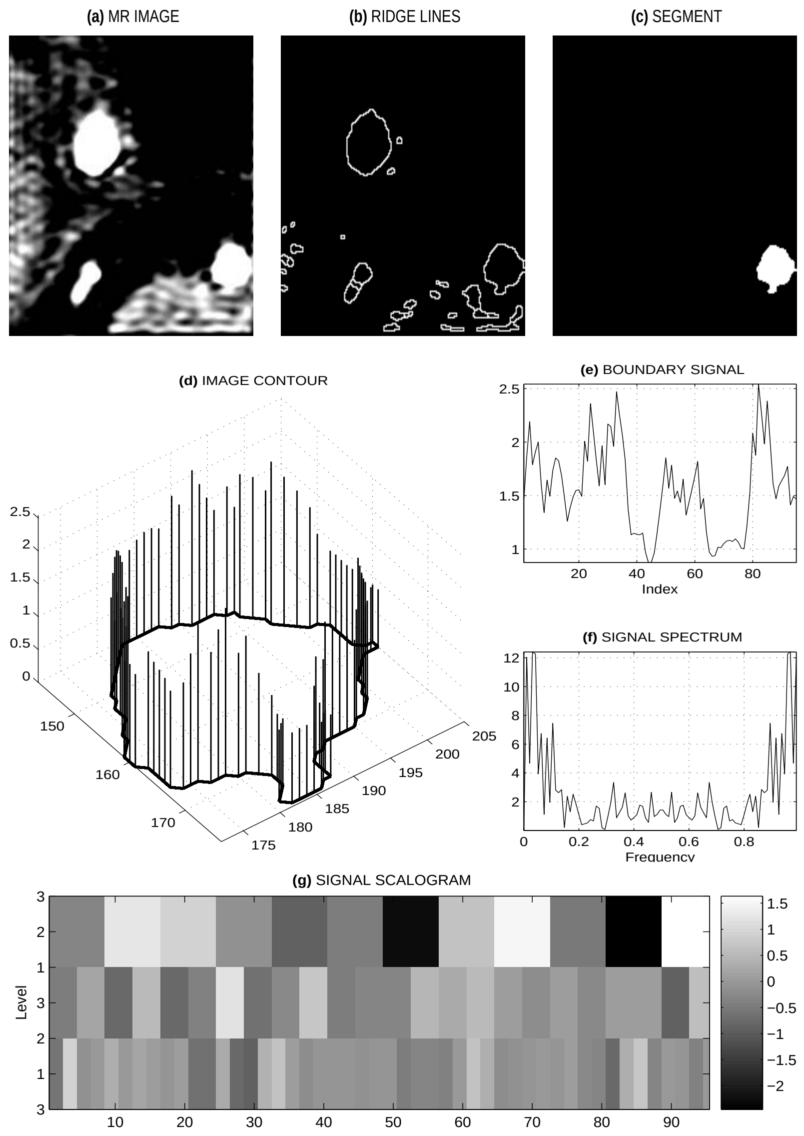

Fig. 8. Results of processing of the magnetic resonance image region of the brain presenting **(a)** original MR image, **(b)** ridge lines separating image components, **(c)** a selected image component representing a vein, **(d)** the boundary signal of the vein, **(e)** the same boundary signal in two dimensions, **(f)** its discrete Fourier transform, and **(g)** its wavelet decomposition into three levels by Daubechies functions

It is possible to summarize that the watershed transform is able to detect most of image segments even though the problem of fault class boundaries can arise in some cases. The proper segmentation is the fundamental task for further image analysis.

Image segments features estimation has been performed both by (i) processing of regions boundary signals and by (ii) analysis of regions textures. In both cases FFT and DWT have been applied. Results obtained have been compared by the variance of features that were lower in the case of the DWT owing to the flexibility of wavelet functions selection that enable more reliable classification.

6 Conclusion

The paper presents the possibility of wavelet transform application for image decomposition, resolution enhancement and image segments feature detection to allow the following image regions classification. The multi-resolution properties of wavelet transform can be used to obtain better results than that achieved by the discrete Fourier transform.

Methods discussed in the paper have been applied to analysis of shapes of biomedical images. Similar methods can be used in other applications in a wide range of interdisciplinary problems of texture analysis including analysis of microscopic images, processing of satellite images, communications and remote earth observations. Further research will be devoted to the two dimensional wavelet transform use for detection of patterns of individual segment textures.

Acknowledgments

The work has been supported by the research grant of the Faculty of Chemical Engineering of the Institute of Chemical Technology, Prague No. MSM 6046137306.

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