Wavelet Transform in Image Regions Classification

ICT PRAGUE

Aleš Procházka, Eva Hošťálková, and Andrea Gavlasová

Institute of Chemical Technology in Prague
Dept of Computing and Control Engineering

http://dsp.vscht.cz/

Abstract

Texture segmentation and classification form challenging topics of the interdisciplinary area of digital signal processing with applications including the analysis of microscopic, biomedical, satellite, or other types of images. In this work, we describe a pattern recognition procedure consisting of image preprocessing, segmentation exploiting the watershed transform, feature extraction, and segments classification using artificial neural networks. Our aim is to emphasize the possibilities of the wavelet transform in the stages of preprocessing and features extraction. The proposed methods are verified for simulated images and subsequently applied to real biomedical images to detect and classify the depicted tissues.

1. Introduction

Pattern recognition procedure

1. Image preprocessing
   - Noise reduction - Discrete Wavelet Transform (DWT) [3, 6]
   - Contrast enhancement etc.
2. Segmentation: distance transform, watershed transform [4]
3. Feature extraction [1, 5]: DWT, Discrete Fourier Transf. (DFT)
4. Classification: artificial neural networks [2]

2. Noise Reduction

Additional noise model of a noisy wavelet coefficient observation

$$w(k) = y(k) + n(k)$$

where $y(k)$ and $n(k)$ correspond to the noise-free signal and iid Gaussian noise, resp., for $k = 0, 1, \ldots, N-1$. N is the no. coefficients.

Wavelet shrinkage algorithm for image smoothing [3]

1. MAD estimate of the standard deviation for iid Gaussian noise

$$\hat{\sigma}_{mad} = median\{|w_j(0)|, |w_j(1)|, \ldots, |w_j(N_j-1)|\} / 0.6745 \quad (1)$$

where $w_j(k)$ are wavelet coefficients of all subbands of level j for $k = 0, 1, \ldots, N_j - 1$

2. Universal threshold for each decomposition level j

$$\delta_j^{(s)} = \sqrt{2\,\hat{\sigma}^2_{mad}\, log(N_j)} \quad (2)$$

3. Soft thresholding to obtain denoised coefficients $\hat{y}_j(k)$

$$\hat{y}_j(k) = \begin{cases} sign\{w_j(k)\} \cdot (|w_j(k)| - \delta_j^{(s)}) & for \;\; |w_j(k)| > \delta_j^{(s)} \\ 0 & otherwise \end{cases} \quad (3)$$

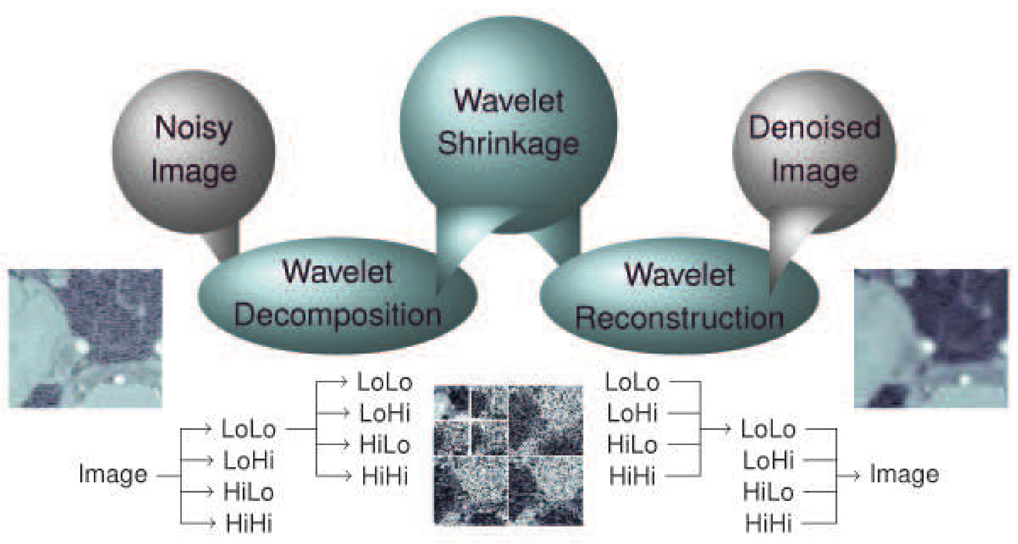


Fig. 1. Noise reduction in biomedical images by shrinking wavelet coefficients from 2 decomposition levels

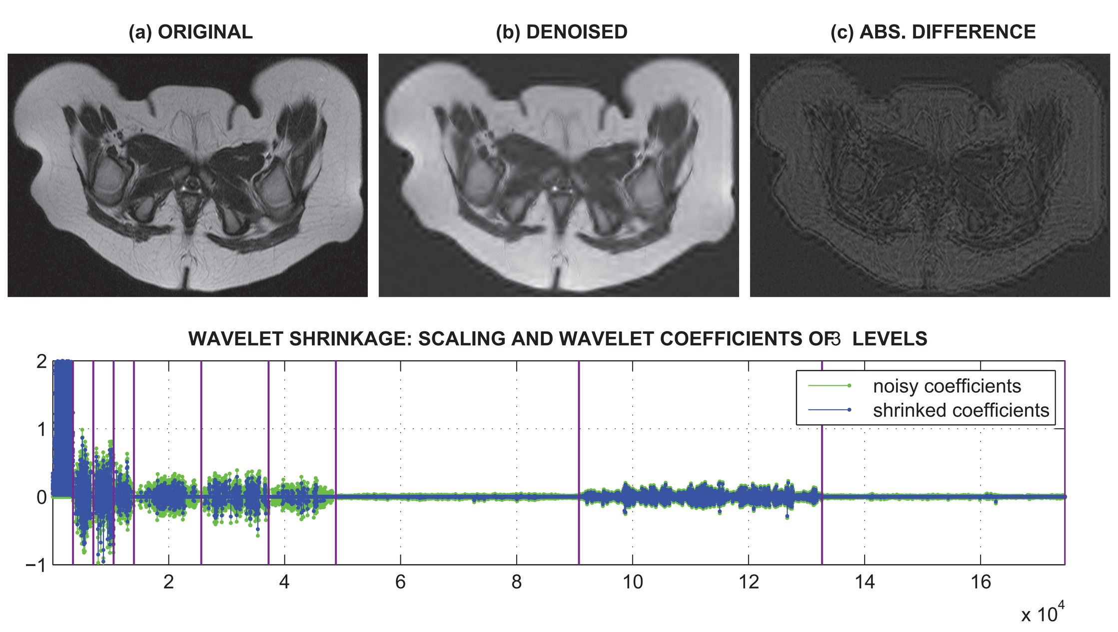


Fig. 2. Smoothing biomedical images by shrinking wavelet coefficients of 3 levels using b-splines biorthogonal wavelets bior5.5

3. Segmentation

Image segmentation by the watershed method [4]

1. Conversion a to black & white image by thresholding
2. Distance transform
   - Assigns to each pixel a value of the Euclidean distance between the pixel and its nearest nonzero neighbour
3. Watershed transform
   - Identifies ridge lines and separates the watershed regions
   - Results in a matrix of labeled regions separated by the watershed pixels lines

4. Feature Extraction

The classification process requires a pattern matrix $\mathbf{P}$ containing features extracted from separate image segments.

Methods used feature extraction [5]

- A chosen transformation of the boundary signal of each segment identified by the watershed transform

Methods of features computation

- *DFT-based features*
  1. The mean of the scaling coefficients
  2. The mean abs. value of the detail coefficients from level 1
- *DWT-based features*
  1. The mean magnitude of the low-frequency coefficients from the interval $\langle 0; F_s/8 \rangle$, where F_s is the sampling frequency
  2. The mean magnitude of the high-frequency coefficients from the interval $\langle F_s/4; F_s/2 \rangle$
- *Combined features* (best performing combination of the above)
  1. DFT-based features 2
  2. DWT-based features 1

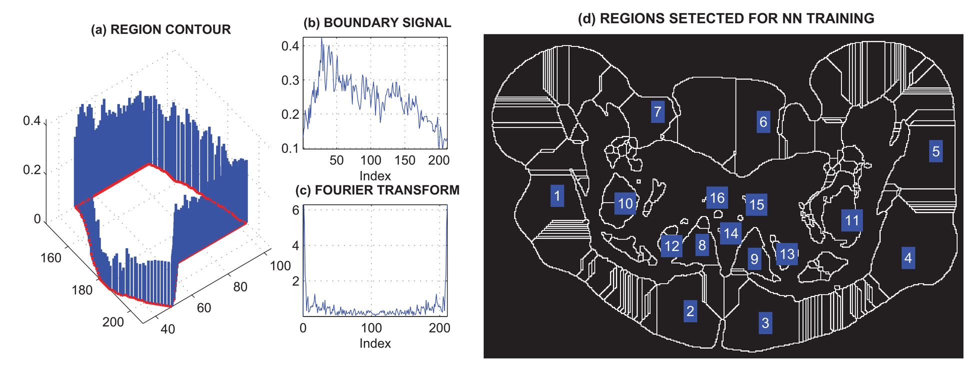
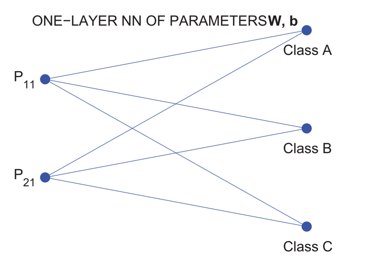


Fig. 3. DFT-based features extraction using the 1-dimensional boundary of a selected region **(a, b, c)** and the watershed regions selected for the neural network training **(d)**

Classification

Classification using self-organizing neural networks [2]

- Classification of Q segments using R features organized in pattern matrix $\mathbf{P}_{R,Q}$
- The no. classes S equals the no. output layer elements



- The learning process
  - The weights matrix $\mathbf{W}_{S,R}$ is recursively recalculated to minimize the distances between each input vector and the corresponding weights of the winning neuron (with coefficients closest to the current pattern)
  - Successful when the network weights belonging to separate output elements represent typical class individuals

The Cluster Segmentation Criterion (CSC)

- Proposed for results evaluation
- Each class $i = 1, 2, \cdots, S$ comprising N_i-segments can be characterized by the mean Euclidean distance $Dist$ of the column feature vectors $\mathbf{p}_{j_k}$ of class segments j_k for $k = 1, 2, \cdots, N_i$ from the class center in the i-th row of matrix $\mathbf{W}_{S,R} = [\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_S]'$ by relation

$$ClassDist(i) = \frac{1}{N_i} \sum_{k=1}^{N_i} Dist(\mathbf{p}_{j_k}, \mathbf{w}_i) \quad (4)$$

- The mean value of average class distances related to the mean value of class centers distances

$$CSC = mean(ClassDist) / mean(Dist(\mathbf{W}, \mathbf{W}')) \quad (5)$$

- Gives low values for compact and well separated clusters and high values for close clusters with extensive dispersion

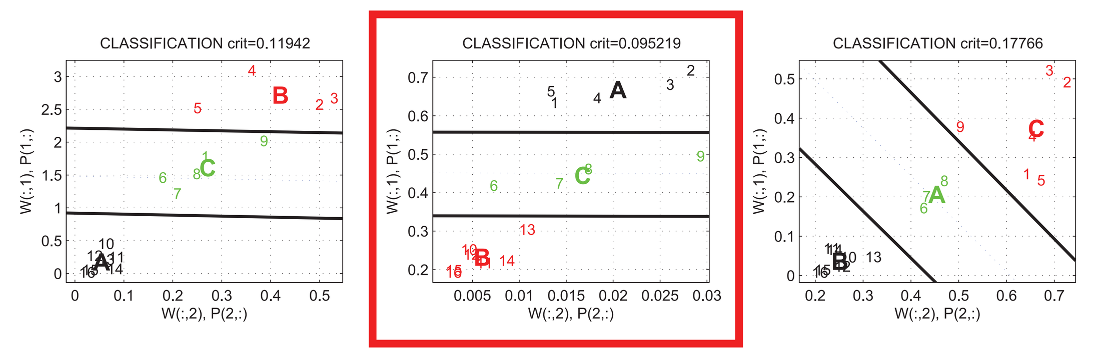


Fig. 4. Comparison of the classification results after smoothing for the DFT, DWT, and combined features (from left to right) extracted from the regions depicted in Fig.3d and used for training of the neural network. Linear class boundaries are defined by the weight matrix $\mathbf{W}_{S,R}$ for $R = 2$ evaluated by a special algorithm which divides the plane into $S = 3$ class sections.

Results

Table 1. COMPARISON OF FEATURES COMPUTATION METHODS ACCORDING TO THE CSC CRITERION VALUE

Smoothing	*DFT Features*	*DWT Features*	*Combined Features*
Yes	0.12	0.10	0.18
No	0.14	0.11	0.14

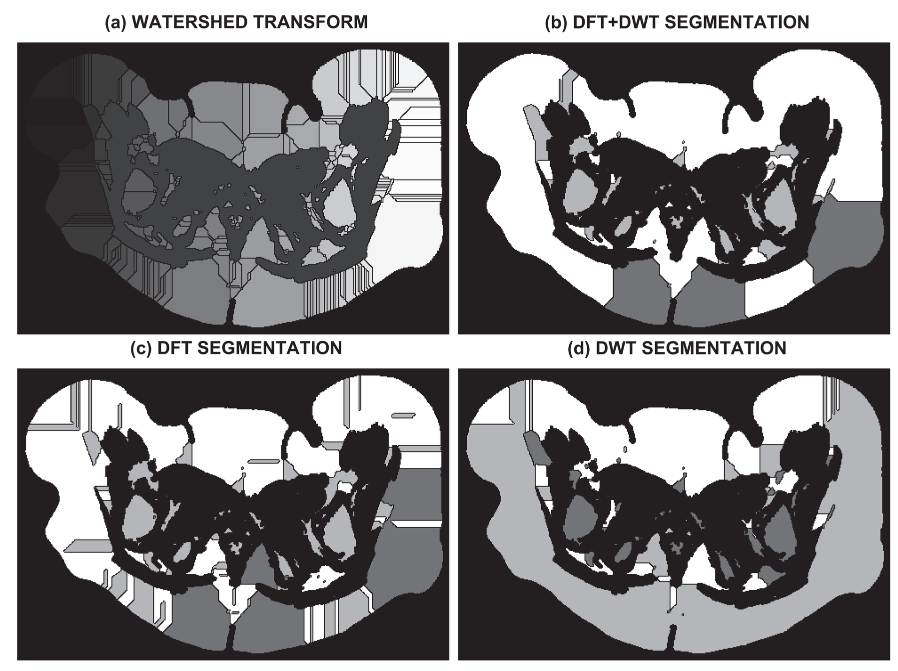


Fig. 5. Classification of the MR image into 3 classes and the background (black) **without smoothing**

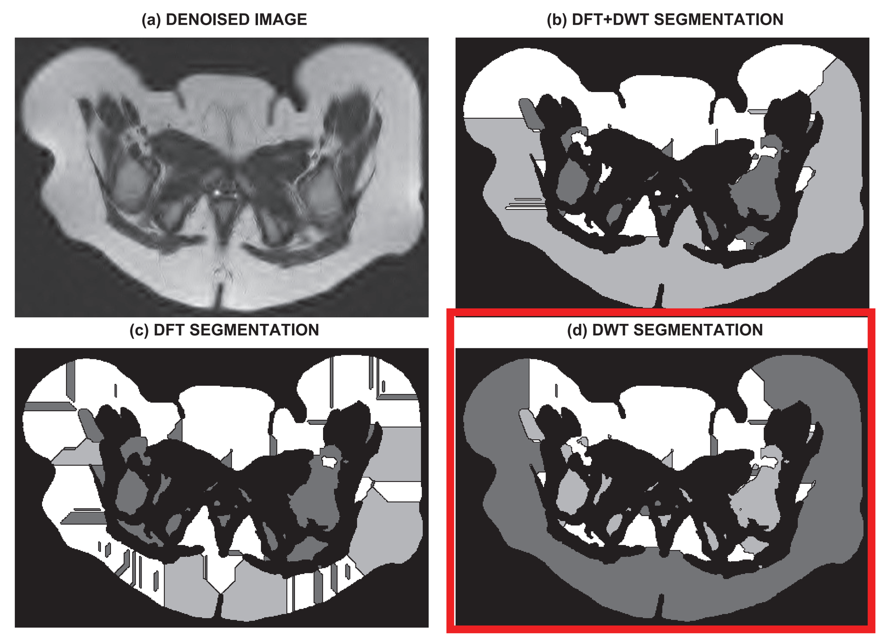


Fig. 6. Classification of the MR image into 3 classes and the background (black) **after smoothing**

Conclusions

- We demonstrated the application of the above methods to real biomedical magnetic resonance data
- The watershed transform detected most of image regions, however, revealed oversegmentation
- We selected 3 pairs of techniques for features computation from regions boundaries and provided the comparison of these techniques using the CSC criterion
- Amongst the 3 feature extraction techniques, the DWT-based method performed best both with and without image smoothing as a preprocessing step
- The DWT transform was also implemented in the smoothing process which had a positive impact on the watershed segmentation results

References

[1] S. Arivazhagan and L. Ganesan. Texture Classification Using Wavelet Transform. *Pattern Recogn. Lett.*, 24(9-10):1513–1521, 2003.

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

[3] D. B. Percival and A. T. Walden. *Wavelet Methods for Time Series Analysis*. Cambridge Series in Statistical and Probabilistic Mathematics. Cambridge University Press, New York, U.S.A., 2006.

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

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

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

8th International Conference
on Mathematics in Signal Processing

IMA

Royal Agricultural College & IET, Cirencester

16 – 18 December 2008

Work was supported by research grant MSM 6046137306.