Functional Transforms in MR Image Segmentation

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***Abstract*—Image segmentation, feature extraction and image components classification form a fundamental problem in many applications of multi-dimensional signal processing. The paper is devoted to the use of watershed transform for image segmentation in connection with wavelet transform allowing image de-noising and image components feature extraction. Proposed methods are applied for biomedical image analysis and processing. The study of MR image segmentation devoted to the detection of its specific components results in the proposal of the appropriate image preprocessing to reduce problems of its oversegmentation. Resulting algorithms include the use of wavelet transform and gradient methods in the preprocessing stage. Proposed algorithms are verified for simulated images and applied for a selected MR biomedical images containing different structures.**

***Index Terms*—Image de-noising, image segmentation, watershed transform, distance transform, discrete wavelet transform, image classification, feature based segmentation, biomedical image processing**

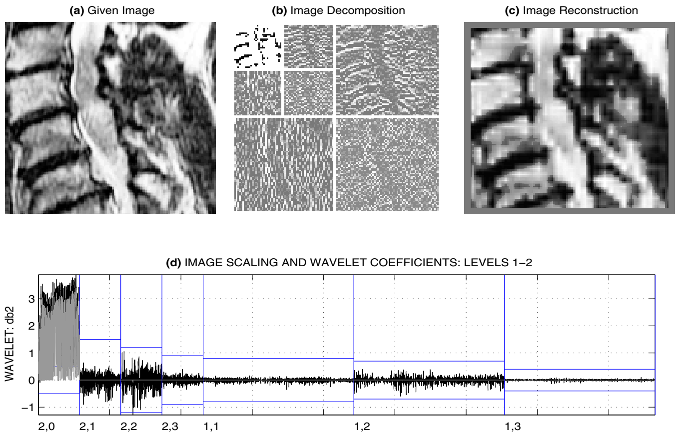

Fig. 1. Image de-noising presenting **(a)** the original image, **(b)** its decomposition, **(c)** reconstruction, and **(d)** scaling and wavelet coefficients thresholding

I. Introduction

Methods of image segmentation [1], [2] form an essential step in advanced techniques of multi-dimensional signal processing. Texture analysis forms an important problem in many tasks including scene classification, shape determination or image processing.

The paper describes the watershed technique of image segmentation and compares results achieved with those obtained using wavelet transform for image de-nosing and extraction of features associated with individual image pixels. For the image decomposition and feature extraction the different analysing functions have been applied.

The initial part of the paper is devoted to a brief description of wavelet transform forming a mathematical tool for image decomposition and reconstruction, de-noising, compression to a selected level and image pixels features extraction. The proposed algorithm of the wavelet image decomposition includes image feature based segmentation and comparison of results with those obtained by the watershed and distance transforms to reduce the problem of image oversegmentation [3].

Individual methods have been verified for simulated images and then applied for processing of selected magnetic resonance biomedical images including images of the brain presented in Fig. 1(a) presenting the process of its de-noising as well.

II. Mathematical Methods of Image De-noising

Image de-noising forms a very important initial step of image preprocessing allowing reduction of different image artifacts. *Discrete Wavelet Transform* (DWT) forms a very efficient tool used for global or local image de-noising used in many cases. Image segmentation and image components classification is then applied in the second step of image processing.

Signal wavelet decomposition using DWT as an alternative to the Discrete Fourier Transform (DFT) results in decomposition into two-dimensional functions of time and scale [4]. The main benefit of DWT over DFT is in its multi-resolution time-scale analysis ability.

Wavelet functions used for signal analysis are derived from the initial (mother) function $h(t)$ forming basis for the set of functions dilated by value $a = 2^m$ and translated by constant $b = k\, 2^m$ for integer values of m, k.

Wavelet dilation closely related to spectrum compression according to Fig. 2 enables local and global signal and image analysis with different resolution level.

The decomposition stage includes the processing of the image matrix $\mathbf{A_{i,j}}$ by columns at first using wavelet (high-pass) and scaling (low-pass) function followed by row down-sampling by factor 2 at first.

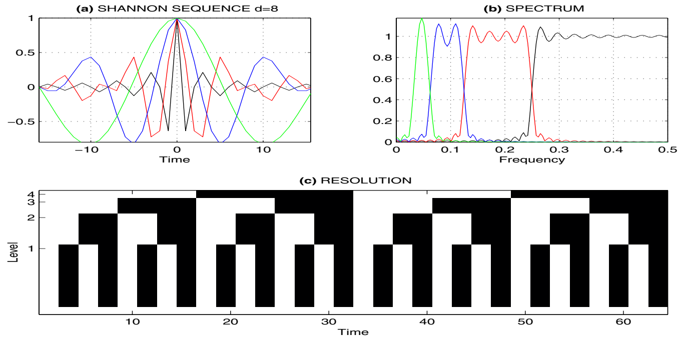

Fig. 2. Wavelet transform principle presenting **(a)** the set of selected (Shannon) wavelet functions, **(b)** the effect of wavelet function dilation to its spectrum compression, and **(c)** localisation of wavelet transform coefficients in the time-scale space

In the following decomposition stage 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 same process can be then applied to the low-low subimage halving subimage sizes again. This process of image decomposition up to the second level is presented in Fig. 1(b) with decomposition coefficients $c(k)$ organized in the row vector given in Fig. 1(d).

The reconstruction stage includes row upsampling by factor 2 at first and row convolution in the initial step. The corresponding images are then summed. The final step assumes column upsampling and convolution with reconstruction filters followed by summation of the results again. In the case of the higher order decomposition this process is repeated.

Image de-noising can be achieved by appropriate thresholding of wavelet coefficients. In the case of soft-thresholding it is possible to evaluate new coefficients $\overline{c}(k)$ using original coefficients $c(k)$ for a chosen threshold value δ by relation

$$\overline{c}(k) = \begin{cases} \text{sign } c(k)\ (|c(k)| - \delta) & \text{if } |c(k)| > \delta \\ 0 & \text{if } |c(k)| \leq \delta \end{cases} \quad (1)$$

This approach can be exploited for both signals and images using different methods of threshold level estimation. Fig. 1(d),(c) provide results of image de-noising using local thresholding.

III. Watershed Segmentation

The watershed transform is useful for many different image segmentation applications. In geography the *watershed* represents the ridge that divides areas drained by different river systems. 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 to enable solution of a variety of image segmentation problems. Understanding of the watershed transform requires us to consider a gray-scale image as a topological surface, where the values of $f(x, y)$ are interpreted as heights. The watershed transform finds the catchment basins and ridge lines in such 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 in [5], [6] for instance.

In the case of medical image analysis it has important drawbacks - over-segmentation in consequence of noise sensitivity.

A. *Watershed Segmentation Using Distance Transform*

The *distance transform* is the common tool used together with the watershed transform. The distance transform of a binary image is a relatively simple concept [6]. Transformation of the binary image $A_{M,N}$ is computed as Euclidean distance of each pixel $a_{i,j}$ to the nearest pixel $a_{k,l}$ with the value 1. Resulting matrix $\mathbf{B_{M,N}}$ is then formed by elements

$$b_{i,j} = \begin{cases} 0 & \text{for } a_{i,j} = 1 \\ \min\limits_{\forall k,l,a_{k,l}=1} \left(\sqrt{(i-k)^2 + (j-l)^2} \right) & \text{for } a_{i,j} = 0 \end{cases} \quad (2)$$

for $i = 1, 2, \cdots, M$, $j = 1, 2, \cdots, N$. An example of the application of the distance transform defined by Eq. (2) applied to matrix $\mathbf{A}$ results in the following matrix $\mathbf{B}$.

1	1	0	0	0	0.00	0.00	1.00	2.00	3.00
1	1	0	0	0	0.00	0.00	1.00	2.00	3.00
0	0	0	0	0	1.00	1.00	1.41	2.00	2.24
0	0	0	0	0	1.41	1.00	1.00	1.00	1.41
0	1	1	1	0	1.00	0.00	0.00	0.00	0.00
Binary image A					**Transformed image B**				

To use the distance transform we have to convert the original gray-scale image to binary image at first using optimal global image threshold by the Otsu's method [7]. In the next step image complement is defined. Image transform using the watershed method should be applied to a matrix after its proper preprocessing to obtain the best image objects contours.

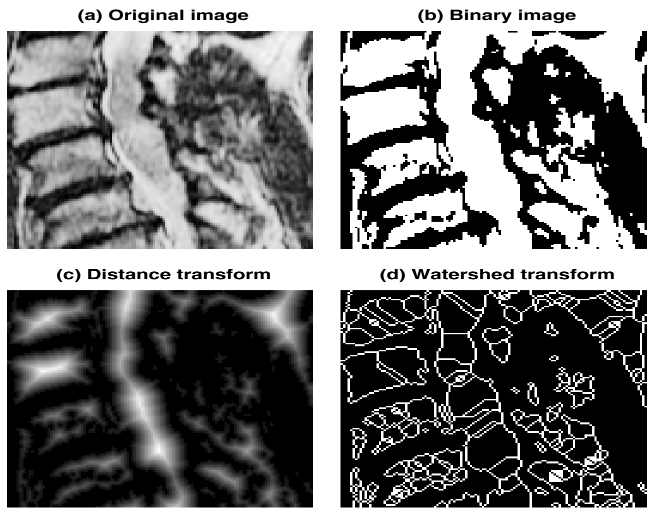

Fig. 3. Process of image segmentation presenting **(a)** the real biomedical image, **(b)** its conversion using thresholding to the binary image, **(c)** application of the distance transform, and **(d)** results of the watershed transform estimating image segments

The matrix processed by the watershed transform results in the next step 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. 3.

B. Watershed Segmentation Using Gradients

The *gradient magnitude* has been used to preprocess a gray-scale image prior to the use of the watershed transform. The gradient magnitude image has high pixel values along object edges, and low pixel values everywhere else [6], [8]. The gradient magnitude is computed using linear filtering methods, in this case using *Sobel* horizontal and vertical edge filter.

The proposed algorithm consists of the estimation of the gradient magnitude of the original image followed by the watershed transform of the gradient. The resulting segmentation is very sensitive to oversegmentation. To reduce this effect the gradient image has been smoothed before the application of the watershed transform. Morphology operation *imopen* removes image elements smaller than the size of structuring element while the morphology operation *imclose* fills the gaps between pixels and smoothes their outer edges. The size of the gaps between pixels must be the maximum of structuring element size [7]. These steps are presented in Fig. 4.

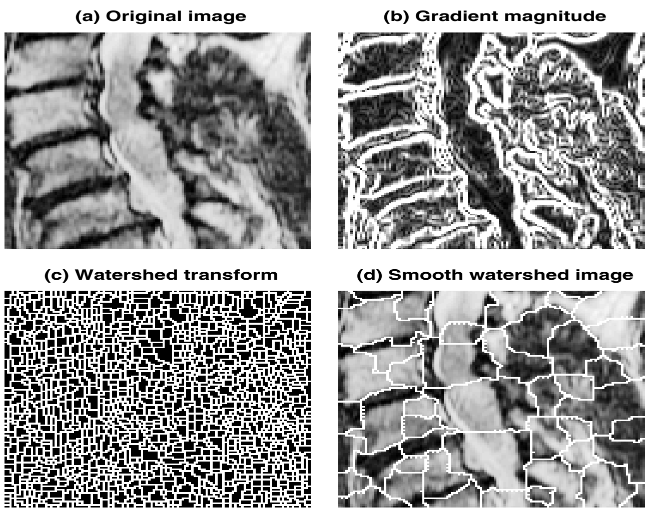

Fig. 4. Results after watershed segmentation using gradients presenting **(a)** the original image, **(b)** corresponding gradient image after the Sobel filter application, **(c)** oversegmented image after watershed transform, and **(d)** resulting image after gradient image smoothing and repeated watershed transform

IV. Feature Based Segmentation

Texture analysis as one of the most important techniques has three primary issues: classification, segmentation and texture shape recovery. Analysis of texture [9] requires the identification of proper attributes or features that differentiate the textures of the image. One of possibilities how to characterize a monochromatic texture is in the analysis of spatial distribution of gray levels in the neighborhood of all its individual pixels.

Texture segmentation based on properties of the neighborhood of root pixels has been studied using co-occurrence features matrices standing for contrast and energy. These matrices are derived for overlapping subimages $\mathbf{B}$ of size $N \times N$ covering the original image both horizontally and vertically.

The algorithm of image features extraction includes

(i) wavelet transform decomposition of each subimage $\mathbf{B}$ of size 4×4 into the first level using selected wavelet function to define the decomposed subimage $\mathbf{C}$ of the same size

(ii) evaluation of features related to subimage $\mathbf{B}$ using relations

$$Energy = \sum_{i,j=1}^{N/2} C_{i,j}^2 \qquad (3)$$

$$Contrast = \sum_{i,j=1}^{N/2} (i-j)^2 C_{i,j} \qquad (4)$$

for approximation of coefficients of each decomposed subimage $\mathbf{C}$

(iii) definition of the features matrix containing values related to each root pixel of the original image

A new matrix has been then evaluated using differences between individual features both in horizontal and vertical directions. Then the segmentation process is started to find texture boundaries.

Artifacts or spurious spots can appear in the image with segmented regions obtained by differentiation. In the case of high differences of feature values within the same region the spots and noise appear. These spurious elements were removed by application of a circular averaging filter. At first the filter with the suitable radius has been created and then applied for a segmented image to minimize these problems.

The processed image is then thresholded using Otsu's method [7] to obtain black and white image. Resulting thick boundaries must then be reduced to one pixel thickness using

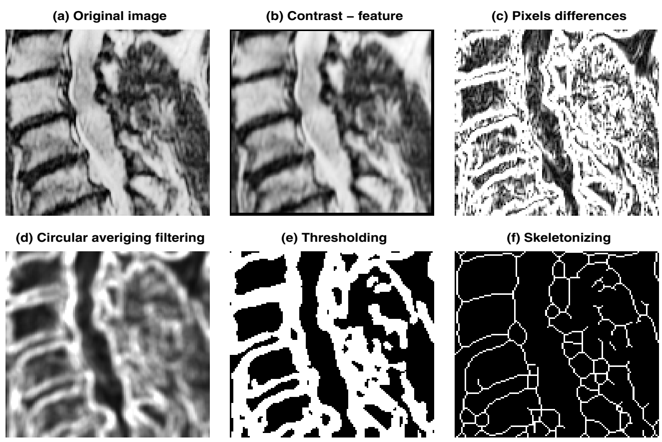

Fig. 5. Feature based image segmentation involves all the segmentation steps using the CONTRAST feature

specific morphology operations. At first operation 'clean' removes isolated pixels - individual 1's that are surrounded by 0's. The second operation 'skel' removes pixels on the boundaries of objects but does not allow objects to break apart. The remaining pixels make up the image skeleton.

V. Results

The segmentation techniques discussed above were applied to two simulated images and to one real biomedical image presented in Fig. 6. These sets of images were segmented using (i) wavelet transform (providing results denoted as a1, a2, a3), (ii) distance transform and watershed transforms (b1, b2, b3), and (iii) gradients and watershed transform (c1, c2, c3).

Problems connected with wavelet segmentation are closely related to thresholding, skeletonizing and selection of optimal thresholding to keep the main image contours. An example of these problems resulting in the skeletonized images are presented in Fig. 6 (a1, a2, a3). Problems of the spurious artifacts are complicated especially for real biomedical images (Fig. 6 (a3)) bringing difficulties to recognize the main image segments.

The watershed transform requires processing of the gray-scale image as a topological surface with its pixel values $f(x, y)$ interpreted as heights. Problems can occur in the identification of the watershed ridge lines in case that values of $f(x, y)$ of the different image regions have the similar heights causing that watershed ridge lines are not detected as in the simulated image in Fig. 6 (b1). On the other hand, too many regions with different values of $f(x, y)$ result in oversegmentation presented in Fig. 6 (b3).

The watershed transform using gradients to image pre-processing is based on edge detection using the Sobel filter in this case. Crossing the region to another one the high (edges) and low (everywhere else) gradients are detected and in the gradient image we get the contours highlight. Many spurious lines result in over-segmentation. Therefore, the gradient image have to be smoothed and then segmented again as presented in Fig. 4. Results of the third technique are presented in Fig. 6 (c1, c2, c3).

VI. Conclusion

The paper presents different methods of biomedical image segmentation. Mathematical analysis and numerical experiments point to the known problem of oversegmentation using the watershed transform. Proposed methods designed to reduce this problem include the use of the original image de-noising and the use of wavelet transform and gradient method for image enhancement. Results achieved are compared with those obtained by wavelet feature based segmentation.

Further studies will be devoted to wavelet based multiresolution segmentation using scaled versions of the original image [10], [11]. The study will include image segmentation methods applied to different levels of image compression. Radon transform and shift invariant wavelet transform [12] will be used as well to detect image features independent to image components rotation and translation.

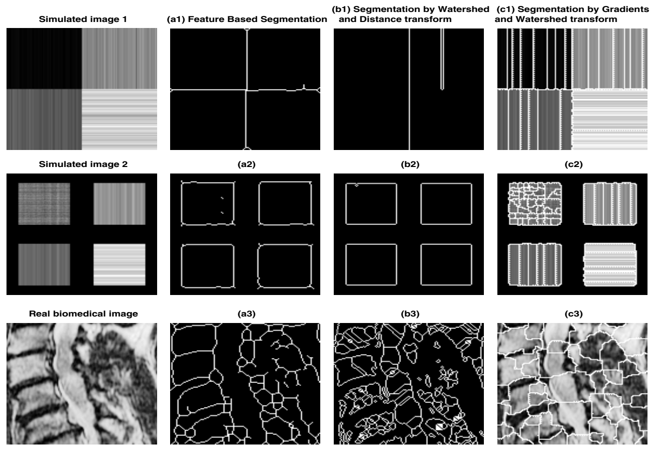

Fig. 6. Segmentation results for simulated textures and a biomedical image presenting ridge lines for **(a)** feature based segmentation, **(b)** distance transform, and **(c)** watershed transform combined with gradients

VII. Acknowledgements

This work has been supported by the Ministry of Education of the Czech Republic (program No. MSM 6046137306). All MR images were kindly provided by the Neurocenter Caregroup.

References

[1] V. Grau, A.U.J. Mewes, A. Alcaniz, R. Kikoinis, and S.K. Warfield, "Improved Wateshed Transform for Medical Image Segmentation Using Prior Information," *IEEE Transaction on Medical Imaging*, vol. 23, no. 4, pp. 447–458, April 2004.

[2] N.I. Weisenfeld, A.U.J. Mewes, and S.K.Warfield, "Highly Accurate Segmentation of Brain Tissue and Subcortical Gray Matter from New-born MRI ," in *Proc. of the 9th Int. Conference on Medical Image Computing and Computer-Assisted Intervention MICCAI 2006*. 2006, pp. 199–206, Pringer-Verlag, MICCAI.

[3] K.N.R.Mohana Rao and A.G. Dempster, "Modification on Distance Transform to Avoid Over-Segmentation and Under-Segmentation ," in *Proc. of the 4th EURASIP-IEEE Symposium on Video/Image Processing and Multimedia Communications*. 2002, pp. 295–301, EURASIP.

[4] 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.

[5] A. Gavlasová, A. Procházka, and M. Mudrová, "Wavelet Use for Image Classification," in *Proc. of the 15th Int. Conf. on Process Control, Štrbské Pleso*. 2005, The Slovak Society of Cybernetics and Informatics.

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

[7] The Mathworks, Inc., 3 Aplle Hill Drive, Natick, MA 01760-2098, *Image Processing Toolbox User's Guide*, 5 edition, 1993 – 2006.

[8] Chen Jia-xin and Liu Sen, "A Medical Image Segmentation Method BAsed on Watershed Transform," in *Proc. of the 5th Int. Conference on Computer and Information Technology*. 2005, pp. 634–638, IEEE.

[9] S. Arivazhagan and L. Ganesan, "Texture Segmentation Using Wavelet Transform," *Pattern Recognition Letters*, vol. 24, no. 16, pp. 3197–3203, December 2003.

[10] M. G. Mostafa, T. F. Gharib, and coll., "Medical Image Segmentation Using a Wavelet-Based Multiresolution EM Algorithm," *IEEE Int. Conf. on Industrial Electronics Technology & Automation*, December 2001.

[11] Haiuha Liu, Zhouhui Chen, Xinhao Chen, and Yaguang Chen, "Multiresolution Medical Image Segmentation Based on Wavelet Transform," in *Proc. of the 27th Annual Conference on Engineering in Medicine and Biology, Shanghai, China*. 2005, pp. 3418–3421, IEEE.

[12] A. Procházka, A. Gavlasová, and I. Šindelářová, "Wavelet Transform in Biomedical Image Segmentation and Classification," in *Proc. of the 6th Int. Workshop on Information Processing in Cells and Tissues, York, UK*. 2005, pp. 395–404, IEE.