Wavelet Use for Reduction of Watershed Transform Over-Segmentation in Biomedical Images Processing

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***Abstract*— Problems of multi-dimensional signal enhancement, segmentation, feature extraction and components classification is essential in many engineering and biomedical applications. The paper is devoted to the use of watershed transform and wavelet transform for MR image components detection and discussion of over-segmentation problems. The goal of the paper is in (i) analysis of image de-noising, (ii) discussion of image enhancement, and (iii) multi-resolutional approach application for reduction of over-segmentation problems. Proposed algorithms include the use of wavelet transform and gradient methods in the preprocessing stage and application of the watershed transform for enhanced images. Resulting algorithms are verified for simulated images and applied for a selected MR biomedical images containing different structures.**

I. INTRODUCTION

Image segmentation methods and texture analysis form essential steps in advanced techniques of multi-dimensional signal processing [1], [2], [3], [4], [5], [6]. 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 use the discrete wavelet transform is studies in connection with image decomposition and reconstruction, denoising, compression to a selected level and image pixels features extraction. The proposed algorithm of the wavelet image decomposition includes edge detection in the preprocessing stage and comparison of results obtained by the watershed and distance transforms to reduce the problem of image over-segmentation [7].

Methods proposed have been verified for simulated images and then applied for processing of selected magnetic resonance biomedical images including images of the back bone presented in Fig. 1.

II. WAVELET TRANSFORM IN IMAGE DE-NOISING

Image de-noising forms a very important initial step of image preprocessing allowing reduction of different image artifacts. Signal wavelet decomposition using discrete wavelet transform (DWT) is often used in these cases allowing global

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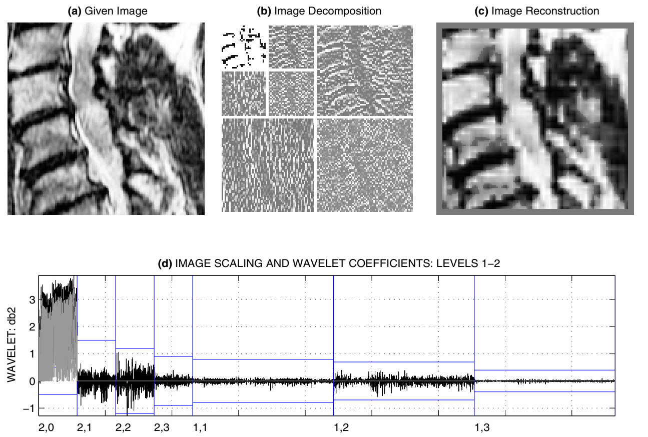

Fig. 1. The process of image de-noising presenting **(a)** the original image, **(b)** its decomposition, **(c)** reconstruction, and **(d)** wavelet coefficients local thresholding

or local image de-noising through signal decomposition into two-dimensional functions of time and scale [8]. The main benefit of DWT over the discrete Fourier transform (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 at different resolution levels.

The decomposition stage includes the processing of the image matrix $\mathbf{A_{i,j}}$ by columns at first using wavelet (high-

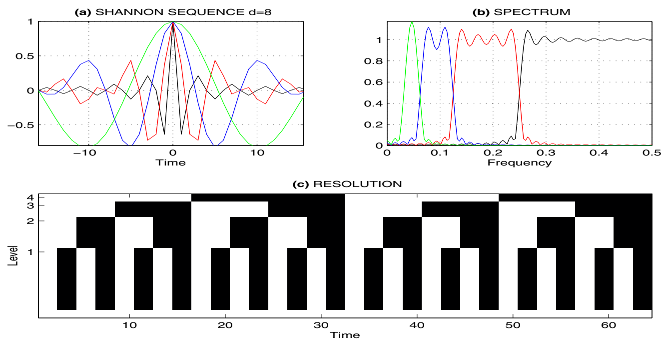

Fig. 2. The principle of the wavelet transform presenting **(a)** the set of selected (Shannon) wavelet functions, **(b)** the effect of wavelet function dilation to its spectrum compression, and **(c)** localisation of wavelet transform coefficients in the time-scale space

pass) and scaling (low-pass) function followed by row downsampling by factor 2 at first. 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

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

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 Transform in Image Segmentation

The watershed transform is useful for different image segmentation applications. In principle it is based upon its geographical meaning of detection of (i) ridges that divide areas drained by different river systems and (ii) catchment basins representing areas from which rainfall flows into a river or reservoir. Understanding the watershed transform requires 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 [9] for instance.

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 [9]. 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

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

for $i = 1, 2, \cdots, M,\ j = 1, 2, \cdots, N$.

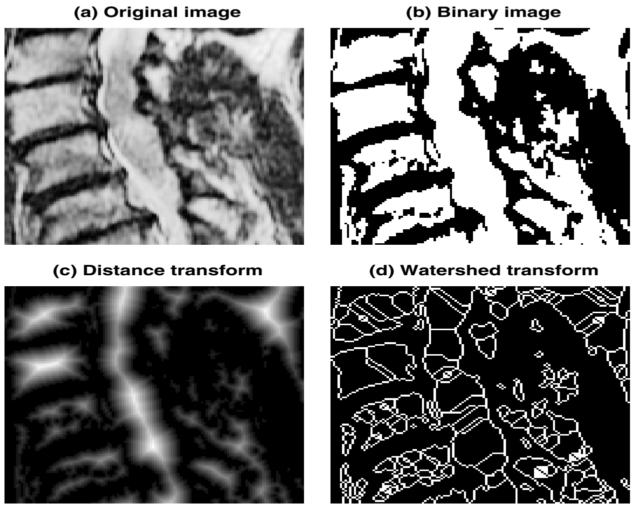

Fig. 3. Process of image segmentation presenting **(a)** the real biomedical image, **(b)** its conversion using thresholding to the binary image, **(c)** application of the distance transform, and **(d)** results of the watershed transform estimating image segments

To use the distance transform it is necesssary to convert the original gray-scale image to binary image at first using optimal global image threshold by the Otsu's method [10]. 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.

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 0 to all nonzero elements with results presented in Figs 3 and 4.

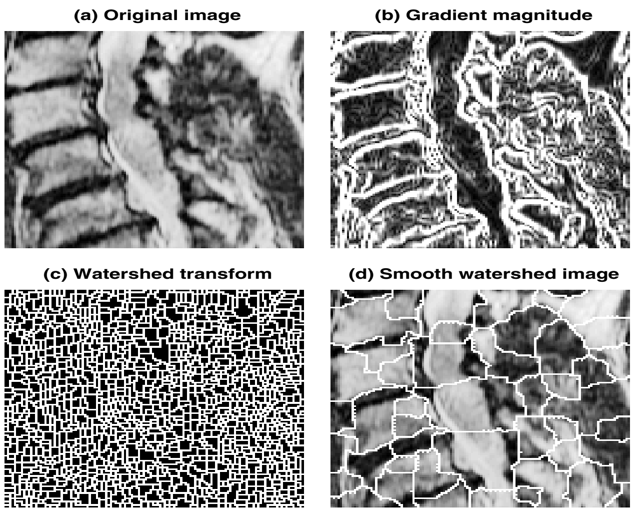

Fig. 4. Results after watershed segmentation using gradients presenting **(a)** the original image, **(b)** corresponding gradient image after the Sobel filter application, **(c)** over-segmented image after watershed transform, and **(d)** resulting image after gradient image smoothing and repeated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

To have the segmentation process more efficient 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 [9], [11]. 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 over-segmentation. To reduce this effect the gradient image has been smoothed before the application of the watershed transform. A specific morphology operations to remove image elements smaller than the size of structuring element and to fill gaps between pixels and smoothes their outer edges have been used. The size of the gaps between pixels must be the maximum of structuring element size [10] according to Fig. 4.

IV. Edge Detection

Image segmentation is closely related to edge detection representing sharp changes of the intensity represented by high frequencies in the Fourier domain. The whole process can be based upon the two-dimensional convolution [12], [13], [14] of the mostly odd-sized convolution kernel $\mathbf{Q}_{K,J}$ and the image matrix $\mathbf{A}_{M,N}$ evaluating the elements b of the new matrix $\mathbf{B}_{M,N}$ given by

$$b_{m-\frac{K-1}{2},n-\frac{J-1}{2}} = \sum_{k=1}^{K}\sum_{j=1}^{J} q_{k,j}\; a_{m-k+1,n-j+1} \tag{3}$$

for all values of m, n and selected boundary conditions. The new value is assigned to the pixel lying in the center of the odd-sized mask at each shift.

Methods of image de-nosing by discrete wavelet transform (DWT) or dual tree complex wavelet transform (DTCWT) can be efficiently combined with edge detection to reduce the effect of noise on gradient methods. This increases the robustness of the whole procedure as depicted in Fig. 5, where the compass (or Robinson) mask is used

$$\mathbf{Q} = \begin{pmatrix} -1 & 1 & 1 \\ -1 & -2 & 1 \\ -1 & 1 & 1 \end{pmatrix} \tag{4}$$

By rotation, this mask approximates the gradient in 8 possible directions. We chose the orientation with the highest value of correlation with the intensity of the pixels in the neighborhood.

In blurred and noisy images, these short-tap filters either fail to detect an edge or tend to give false alarms. However, extending the tap length leads to blurring the originally sharp edges. The problem lies in attempting to detect edges of different spatial sizes by a single-scale filter. It is more convenient to analyze images by multi-scale methods, such as the Canny detector. The Canny filter approximates first derivative of a Gaussian in the direction of the gradient

$$\Delta G(x) = x\; e^{-\frac{x^2}{2\sigma^2}} \tag{5}$$

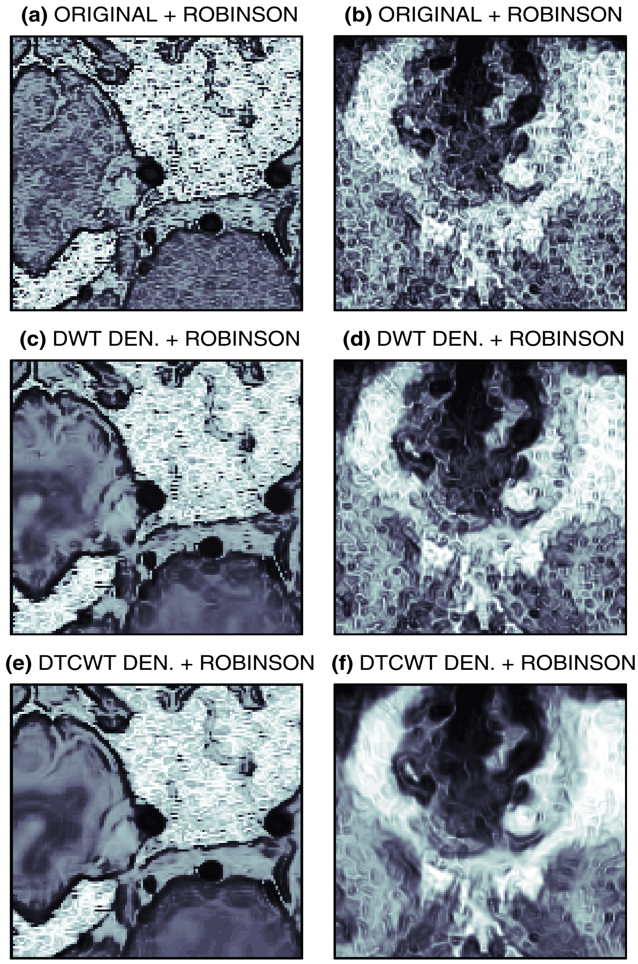

Fig. 5. Convolution of the Robinson filter with **(a)**, **(b)** the original MR and CT brain images, resp., **(c)**, **(d)** the images after DWT de-noising, and **(e)**, **(f)** the images after the DTCWT de-noising

By adjusting the value of σ, this filter operates at various scales. Fig. 6 depicts the Canny method applied to de-noised biomedical images of the brain. The edges are firstly obtained by thresholding the outcome of the convolution. The pixels with the values greater than the higher threshold are declared as edges and the ones with the values smaller than the lower threshold are assigned to edges only if they belong to stronger edges in the neighborhood.

V. Results

Wavelet image de-noising using both the DWT and the DTCWT for different wavelet functions followed by the gradient image enhancement has been applied to selected biomedical images. The main purpose of this process lies in the detection of biomedical image components, their visual enhancement, segmentation and early diagnostics.

To analyse the results, it is possible to study differences between the original and the de-noised images and their histograms. Fig. 7 presents distribution of these differences both for the DWT and the DTCWT used for image decomposition, coefficients thresholding, and reconstruction.

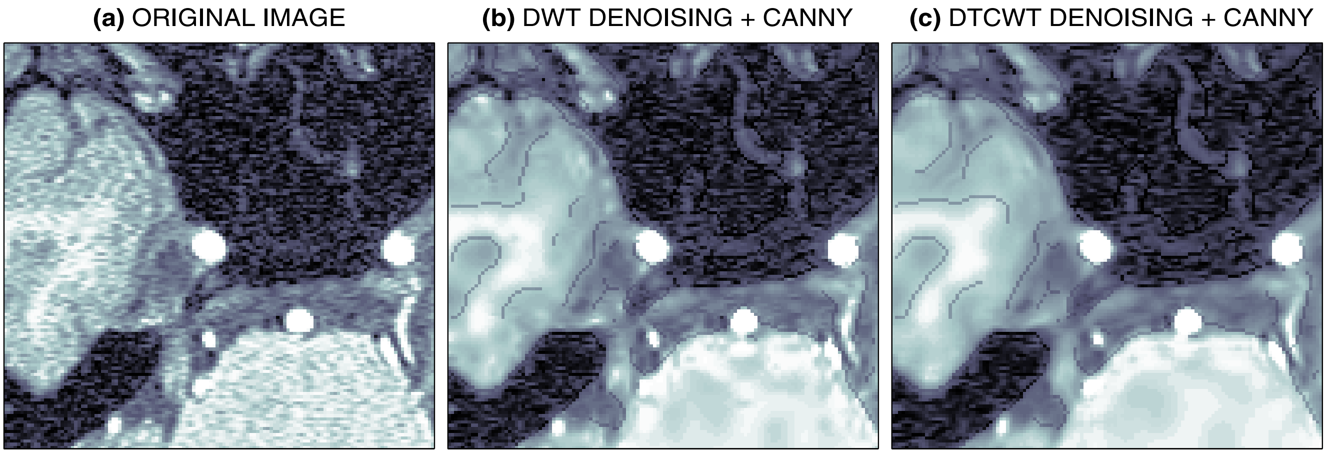

Fig. 6. Axial MR brain image processing presenting **(a)** the original image, **(b)** and **(c)** images processed by the Canny edge detector after de-noising by wavelet shrinkage exploiting the DWT (14-tap symlet filters) and the DTCWT (14-tap q-shift filters), resp.

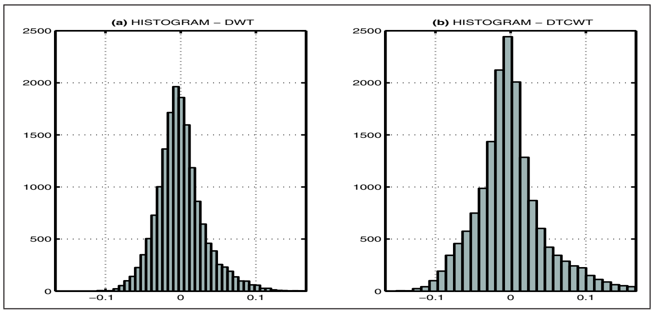

Fig. 7. Histogram of difference images after **(a)** the discrete wavelet transform and **(b)** the dual-tree complex wavelet transform use for original image de-noising

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 [15], [16]. The study will include image segmentation methods applied to different levels of image compression. Radon transform and shift invariant wavelet transform will be used as well to detect image features independent to image components rotation and translation.

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