WAVELET BASED 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 Wavelet transform for feature extraction associated with image pixels and their classification in comparison with the watershed transform. A specific attention is paid to the use of Haar transform as a tool for image compression and image pixels feature extraction. Proposed algorithm is verified for simulated images and applied for a selected MR biomedical image processing in the MATLAB environment.

1 Introduction

Image segmentation is an essential step in many advanced techniques of multi-dimensional signal processing and its applications. Texture analysis occupies an important place in many tasks such as scene classification, shape determination or image processing. This paper describes the technique of wavelet transform use for features extraction associated with individual image pixels and comparison of this method with application of the watershed transform technique. For the image decomposition and feature extraction the Haar transform has been applied as a basic tool used in the wavelet transform. A specific part of the paper is devoted to the mathematical analysis of Haar transform as a tool for image compression and image pixels features extraction using decomposition and reconstruction matrices. The method described is used for description of the whole system enabling perfect image reconstruction. The proposed algorithm of the Haar wavelet image decomposition includes image feature based segmentation and comparison of results with the watershed transform. Individual methods have been verified for simulated images and then applied for processing of selected magnetic resonance biomedical images. All methods were designed in the Matlab environment.

2 Haar Wavelets in Image Decomposition

Wavelets are functions generated from a single function by its dilations and translations. The Haar transform forms the simplest compression process of this kind. In 1-dimension, the corresponding algorithm [4] transforms a 2-element vector $[x(1), x(2)]^T$ into $[y(1), y(2)]^T$ by relation:

$$\begin{bmatrix} y(1) \\ y(2) \end{bmatrix} = \mathbf{T} \begin{bmatrix} x(1) \\ x(2) \end{bmatrix} \qquad \texttt{where} \quad \mathbf{T} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \tag{1}$$

is an orthonormal matrix as its rows are orthogonal to each other (their dot products are zero). Therefore $\mathbf{T}^{-1} = \mathbf{T}^T$ and it is possible [4] to recover $\mathbf{x}$ from $\mathbf{y}$ by relation

$$\begin{bmatrix} x(1) \\ x(2) \end{bmatrix} = \mathbf{T}^T \begin{bmatrix} y(1) \\ y(2) \end{bmatrix} \tag{2}$$

In 2-dimensions $\mathbf{x}$ and $\mathbf{y}$ become 2×2 matrices. We can transform at first the columns of $\mathbf{x}$, by pre-multiplying by $\mathbf{T}$, and then the rows of the result by post-multiplying [4] by $\mathbf{T}^T$ to find

$$\mathbf{y} = \mathbf{T}\,\mathbf{x}\,\mathbf{T}^T \qquad \texttt{and in the next step} \quad \mathbf{x} = \mathbf{T}^T\,\mathbf{y}\,\mathbf{T} \tag{3}$$

To show more clearly what is happening we can use a specific matrix $\mathbf{x}$ of the form

$$\mathbf{x} = \begin{bmatrix} \mathrm{a} & \mathrm{b} \\ \mathrm{c} & \mathrm{d} \end{bmatrix} \qquad \texttt{imlying that} \quad \mathbf{y} = \frac{1}{\sqrt{2}} \begin{bmatrix} \text{a+b+c+d} & \text{a-b+c-d} \\ \text{a+b-c-d} & \text{a-b-c+d} \end{bmatrix} \tag{4}$$

These operations correspond to the following filtering processes:
Top left: 2-D lowpass filter (Lo-Lo).
Top right: horizontal highpass and vertical lowpass filter (Hi-Lo).
Lower left: horizontal lowpass and vertical highpass filter (Lo-Hi).
Lower right: 2-D highpass filter (Hi-Hi).

To apply this transform to a complete image, we group the pixels into 2×2 blocks and apply Eq. (3) to each block. To view the result, all the top left components in Fig. 1(a) of the 2×2 blocks in $\mathbf{y}$ were grouped together to form the top left subimage in Fig. 1(b) and the same for the components in the other three positions. It is clear from Fig. 1(b) that the most of the energy is contained in the top left (Lo-Lo) subimage and the least energy is in the lower right (Hi-Hi) subimage. The top right (Hi-Lo) and the lower left (Lo-Hi) subimage contains [4] the edges.

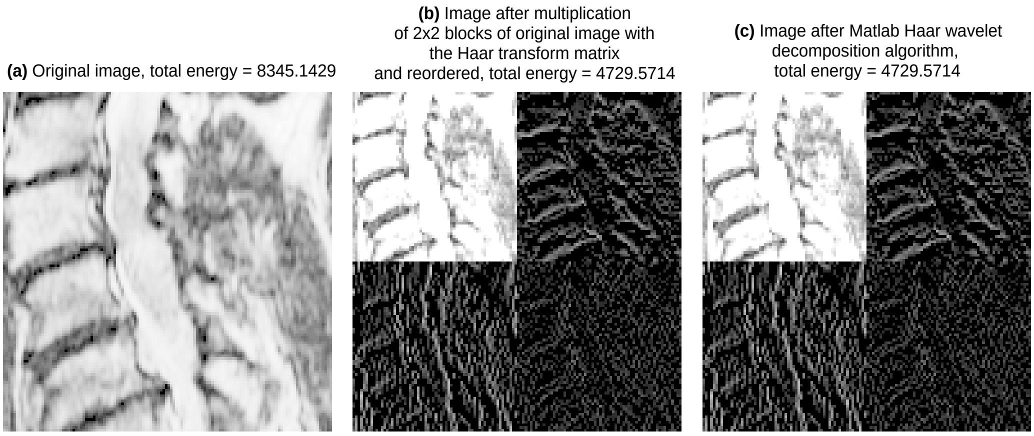

Figure 1: Original image **(a)** was decomposed using wavelet image decomposition by the Haar transform and result **(b)** was obtained by application of Eq. (3) to each 2×2 block after reordering and **(c)** by Matlab wavelet decomposition function

The energies of all four subimages in Fig. 1 having values

Lo – Lo	**Hi – Lo**
$41.73.10^2$	$1.89.10^2$
88.2%	4.0%
Lo – Hi	**Hi – Hi**
$2.97.10^2$	$0.71.10^2$
6.3%	1.5%

point to the most significant compression of energy in the Lo-Lo subimage.

3 Image Segmentation Using Wavelet Transform

Following subsections describe algorithms of image segmentation using wavelet transform with resulting images presented in Fig. 2.

3.1 Image Features Extraction

Texture is characterized by the spatial distribution of gray levels in a neighborhood. An image region has a constant texture if a set of its local properties in that region is constant, slowly changing or approximately periodic. Texture analysis is one of the most important techniques used in analysis. There are three primary issues in texture analysis: classification, segmentation and shape recovery from texture. Analysis of texture [1] requires the identification of proper attributes or features that differentiate the textures of the image.

In this paper, texture segmentation is carried out by comparing co-occurrence matrix features Contrast and Energy of size $N \times N$ derived from discrete wavelet transform overlapping but adjacent subimages $\mathbf{C_{i,j}}$ of size 4×4, both horizontally and vertically.

The algorithm of image features extraction involves

a) decomposition, using one level DWT with the Haar transform, of each subimage $\mathbf{C_{i,j}}$ of size 4×4 taken from the top left corner

b) computation of the co-occurrence matrix features energy and contrast given in Eqs (5) and (6) from the detail coefficients, obtained from each subimage $\mathbf{C_{i,j}}$

c) forming new feature matrices

$$Energy = \sum_{i,j=1}^{N} C_{i,j}^2 \tag{5}$$

$$Contrast = \sum_{i,j=1}^{N} (i-j)^2 C_{i,j} \tag{6}$$

3.2 Pixel Differences

After the computation of co-occurrence matrix features, a new matrix with differences is obtained. It is carrying out by calculation the difference between the value by value of features both in horizontal and vertical directions. Then the segmentation band is formed across the texture boundaries.

3.3 Circular Averaging Filtering

In the image with the segmented band obtained after differences could appear artifacts or spurious spots. When within the same region the high differences of features values appeared, the spots and noise were formed. These spurious elements were removed by applying a circular averaging filter. First the filter with suitable radius was created and then applied for a segmented image to minimize and efface the image.

3.4 Thresholding and Skeletonizing

The processed image is then thresholded using global image threshold using Otsu's method [6] and black and white image is obtained. Because of the thick boundaries we must thin them on the line of one pixel thickness. To process this specific morphology operations were used. 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 pixels remaining make up the image skeleton.

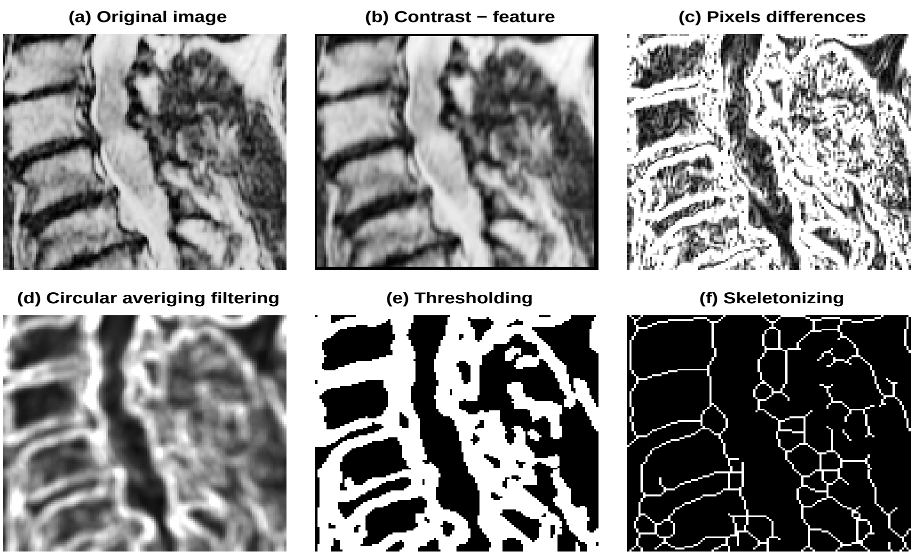

Figure 2: Wavelet based image segmentation involves all the segmentation steps using the CONTRAST feature

4 Watershed Transform

In geography a *watershed* is 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 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 by [2, 3] for instance.

5 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 [3]. It represents the distance from each pixel with its value of 1 to the nearest nonzero-valued pixel as we can see below.

1	1	0	0	0
1	1	0	0	0
0	0	0	0	0
0	0	0	0	0
0	1	1	1	0

Binary image

0.00	0.00	1.00	2.00	3.00
0.00	0.00	1.00	2.00	3.00
1.00	1.00	1.41	2.00	2.24
1.41	1.00	1.00	1.00	1.41
1.00	0.00	0.00	0.00	0.00

It′s distance transform

To use the distance transform we have to convert original gray-scale image to binary image at first using optimal global image threshold using Otsu's method [6]. 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. All zero pixels of the complementary image have been assigned by $-\infty$ at first.

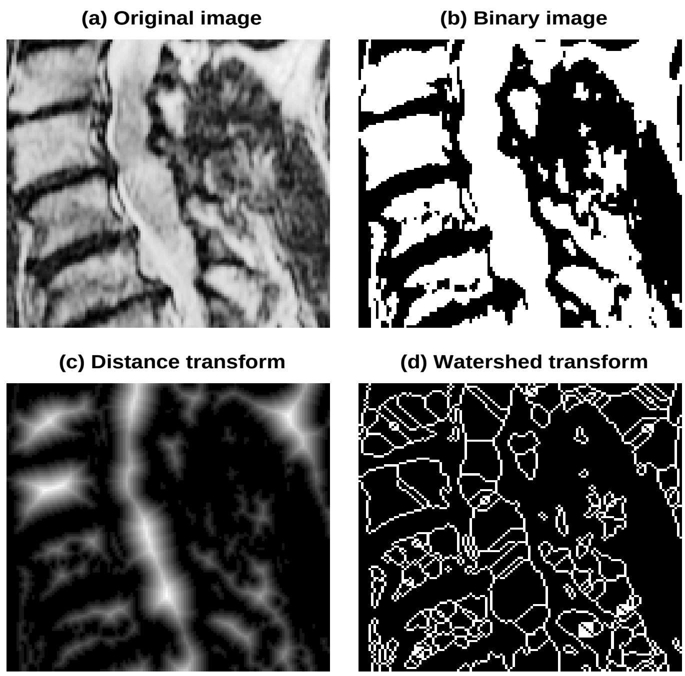

Figure 3: The segmentation technique starts from **(a)** real biomedical image, which is converted by thresholding to **(b)** binary image followed by the application of the distance transform in image **(c)** and the watershed transform **(d)** resulting in estimation of image segments

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. 3.

6 Watershed Segmentation Using Gradients

The *gradient magnitude* is used often to preprocess a gray-scale image prior to using watershed transform. The gradient magnitude image has high pixel values along object edges, and low pixel values everywhere else [3]. The gradient magnitude is computed using linear filtering methods, in this case using *Sobel* horizontal and vertical edge filter.

We start by computing gradient magnitude of original image and then we compute the watershed transform of the gradient. The resulting segmentation is not good as it is very sensitive to over-segmentation. So we must smooth the gradient image before computing its watershed transform. Here we use some *morphology operations* such as *closing* and *opening*. Morphology operation *imopen* removes from the image such elements, which are smaller than the size of structuring element. 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 [6]. These steps are presented in Fig. 4.

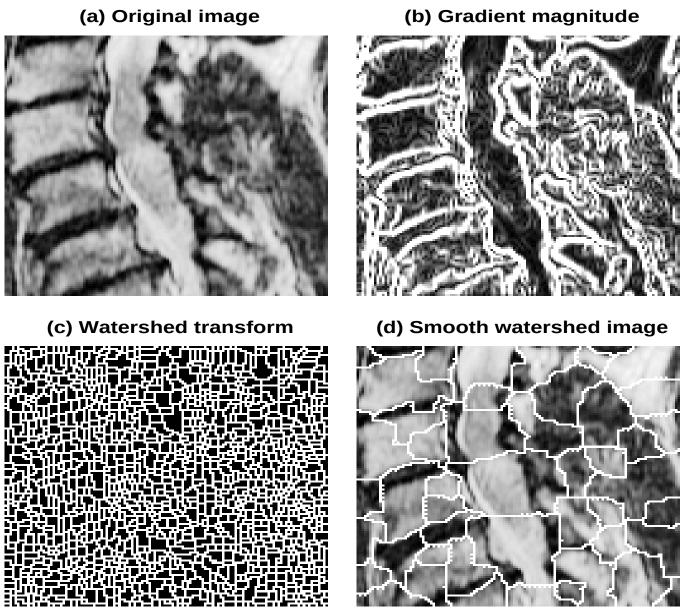

Figure 4: Results after watershed segmentation using gradients present **(a)** original image, its **(b)** gradient image after Sobel filter application, **(c)** over-segmented image after watershed transform and **(d)** resulting image after gradient image smoothing and repeated watershed transform

7 Results

The segmentation techniques discussed in the previous sections were applied on two simulated images and for one real biomedical image of size 128×128. The set of images assigned as **(a1, a2, a3)** were segmented using wavelet transform, as **(b1, b2, b3)** using distance transform and watershed transform, and as **(c1, c2, c3)** using gradients and watershed transform.

Problems connected with wavelet segmentation are closely related to thresholding and skeletonizing. It is important to elect optimal thresholding to keep the main image contours. On the other hand the spurious spots and artifacts were removed. Examples of these problems in resulting skeletonized images are presented in Fig. 5 (a1, a2) and Fig. 5 (a3), where the problems with the spurious artifacts are more visible in the case of real biomedical image Fig. 5 (a3) and it is more difficult to recognize the main image segments. In the case of simulated images in Fig. 5 (a1, a2) there were no problems with region segmentation.

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. There are the problems to identify the watershed ridge lines on the basis in case that the values of $f(x, y)$ of the different image regions have the similar heights. So the watershed ridge lines are not detected. This is in the case of a simulated image in Fig. 5 (b1). On the other hand, too many regions with different values of $f(x, y)$ result in over-segmentation presented in Fig. 5 (b3).

The watershed transform using gradients to image pre-processing is based on edge detection. In this case the Sobel filter is used. 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. 5 (c1, c2, c3).

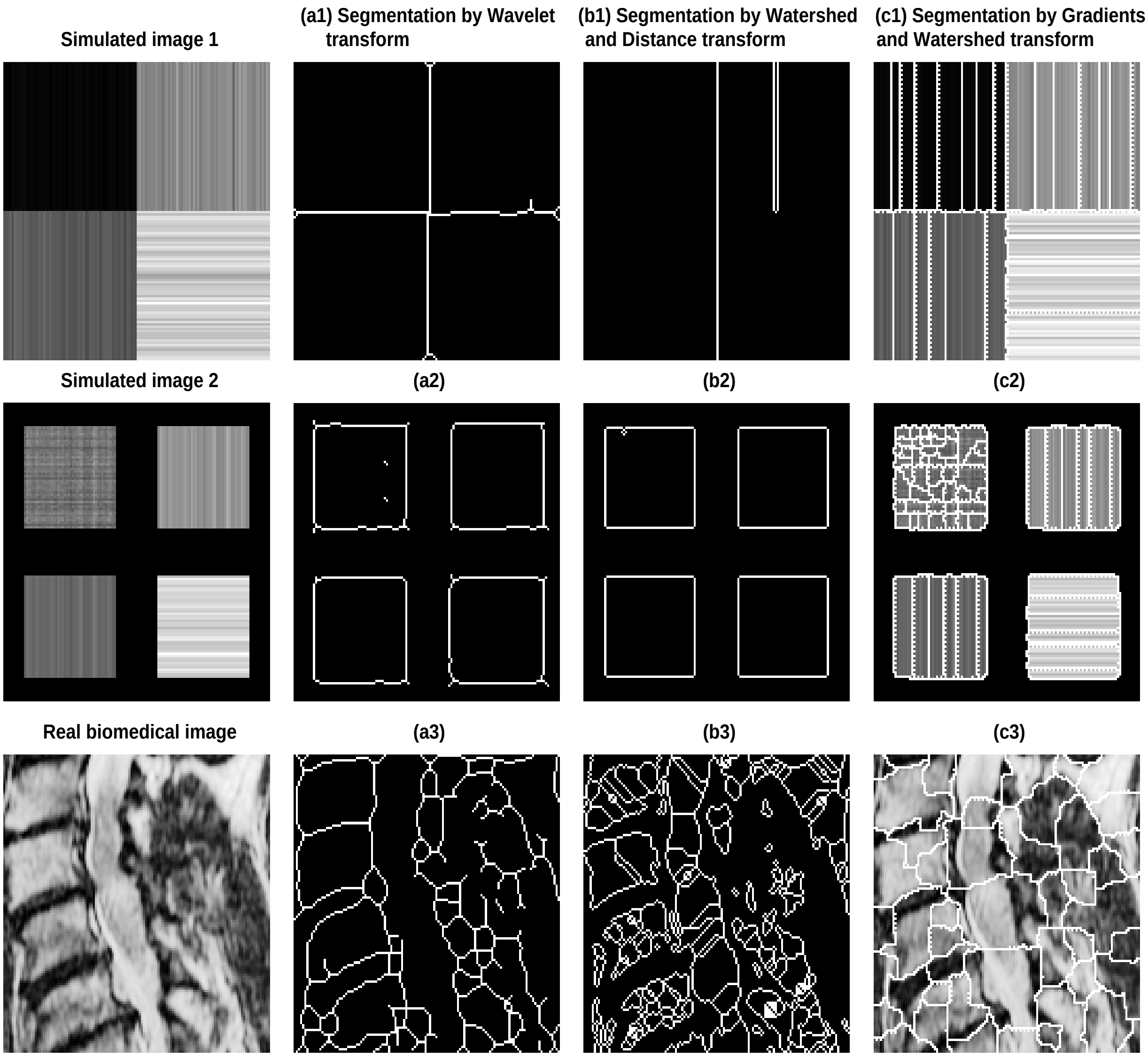

Figure 5: Texture segmentation results presenting comparison of segmentation methods using simulated images and a real biomedical image

8 Conclusion

Further studies will be devoted to wavelet based multiresolution segmentation based on generating scaled versions of the original image using wavelet analysis as described in [5].

9 Acknowledgements

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