Biomedical Image Enhancement, Segmentation and Classification Using Wavelet Transform

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Abstract: Mathematical methods used for analysis of biomedical data include many topics of interdisciplinary general area of digital signal and image processing and they cover algorithmic tools for image enhancement, image components detection and their segmentation using feature vectors estimated either in the space and frequency domains by selected statistical methods and functional transforms. The paper is devoted to specific topics of biomedical image processing based upon the time-scale image decomposition using the set of dilated and translated wavelet functions. Topics covered include (i) the use of wavelet transform for modification of image resolution, (ii) wavelet coefficients thresholding used for image de-nosing, (iii) evaluation of image components features for their classification into the given number of classes using neural networks. Methods proposed are applied for biomedical images to allow another view to their analysis and to contribute to early diagnostics of serious diseases.

Key–Words: Biomedical data processing, wavelet transform, resolution enhancement, contour detection, texture analysis, data de-noising, image components analysis, classification, cluster analysis, neural networks

1 Introduction

A common problem of biomedical multi-dimensional signal processing is in image enhancement, its segmentation and analysis of its components closely connected with object analysis and early diagnostics of serious diseases. These problems are often related also to the selection of appropriate image resolution enabling (i) detection of object details with the specified precision and (ii) compression of information for efficient data processing and their transmission over communication links. Signal resolution choice and the appropriate transform selection is therefore one of basic tasks of signal processing.

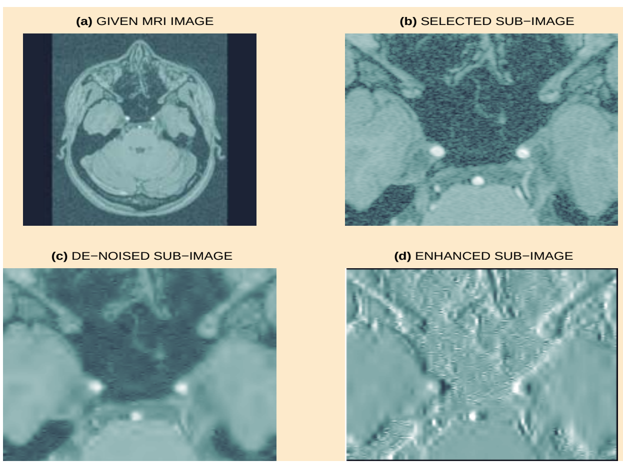

Figure 1: Selected steps of the brain MRI enhancement presenting **(a)** observed image, **(b)** its subregion, **(c)** de-noised sub-image, and **(d)** its enhancement using gradient

Mathematical topics related to biomedical data analysis [7] include general problems of functional transforms in image processing [15, 4] and especially problems of signal de-noising [20], restoration of corrupted regions [9], multi-resolution analysis [17], detection of image objects and evaluation of associated pattern matrix for their classification. Figs 1 and 2 present application of these methods in neurology and analysis of biomedical images using gradient enhancement and wavelet transform studied before [16].

The following paper presents in its main part the use of wavelet transform for image de-noising, its enhancement and analysis to evaluate image components features using their contour signals. The quality of data clusters is then analysed by the proposed criterion with neural networks [5] applied for cluster elements classification using different methods for feature vectors selection.

2 Principle of Image Decomposition

Functional transforms represent basic mathematical tools for multi-dimensional signal processing as they enable signal representation in different spaces [1, 2, 3]. These transforms include traditional Discrete Fourier Transform (DFT) and various further processing tools including Discrete Wavelet Transform

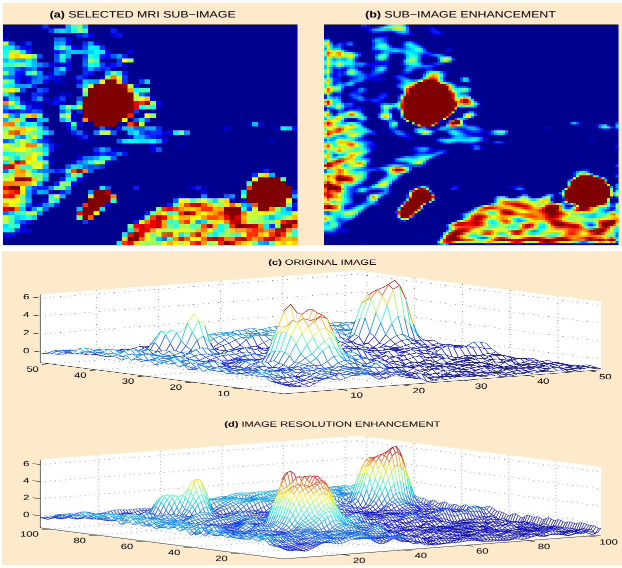

Figure 2: A selected part of the MRI resonance image of the brain presenting **(a)** chosen sub-image with veins, **(b)** sub-image resolution enhancement using the wavelet transform, and **(c)**, **(d)** 3D visualization

(DWT) or the multiscale Dual Tree Complex Wavelet Transform (DTCWT) [19] allowing to analyze signals on different scales with a selected resolution.

The set of wavelet functions can be the same both for signals and images using as a template the mother function $h(t)$ with the possibility of its modification by parameters a and b in the form

$$h_{m,k}(t) = \frac{1}{\sqrt{a}}\, h\left(\frac{1}{a}\,(t-b)\right) \tag{1}$$

In case of often used selection of dilation $a = 2^m$ and translation $b = k\ 2^m$ the set of these functions is defined by relation

$$h_{m,k}(t) = \frac{1}{\sqrt{2^m}}\, h\left(2^{-m} t - k\right) \tag{2}$$

forming the set of functions which for the different dilation parameters enable both the local and the global signal view allowing to analyse either global signal properties or its details.

The similar approach can be applied for a multi-dimensional signal with its values stored in the multi-dimensional matrix. Using this approach it is possible to describe the one-dimensional signal as its special case with its values in one column of such a matrix only. Fig. 3 presents the decomposition tree for an image matrix

$$[\mathbf{g}(n,m)]_{N,M} = [\mathbf{s}_1, \mathbf{s}_2, \cdots, \mathbf{s}_M] \tag{3}$$

formed by column vectors (signals) $\{\mathbf{s}_k(n)\}_{n=0}^{N-1} = [s_k(0), s_k(1), ..., s_k(N-1)]^T$ and $k = 1, 2, \cdots, M$.

The image decomposition assumes the convolution of image matrix with wavelet and scaling functions by columns at first and downsampling by value $D{=}2$ in the first stage. Decomposition functions are represented by the half-band low-pass scaling function

$$\{l(k)\}_{k=0}^{L-1} = [l(0), l(1), \cdots, l(L-1)] \tag{4}$$

and complementary high-pass wavelet function

$$\{h(k)\}_{k=0}^{L-1} = [h(0), h(1), \cdots, h(L-1)] \tag{5}$$

used for convolution in the form

$$sl(n) = \sum_{k=0}^{L-1} l(k)\ s(n-k) \quad sh(n) = \sum_{k=0}^{L-1} h(k)\ s(n-k)$$

for all values of n. The following subsampling by value $D{=}2$ imply that the number of resulting coefficients is equal to its original value. The next decomposition stage is applied to rows with row downsampling. Resulting multi-dimensional signal is formed by four images for all combinations of the low-pass and high-pass processing stages of the initial image according to Fig. 4(b) presenting decomposition into the second level.

Reconstruction processing blocks (Fig. 3) include the row upsampling by value $U{=}2$ followed by row convolution, summation of results and column upsampling by value $U = 2$ followed by column convolution and summation.

The complete DWT can be applied for processing of multi-dimensional signals in the following steps

1. decomposition of an image to allow image analysis and possible compression [13]
2. increase of image resolution [16] for the downsampling coefficient $D = 1$ and upsampling by $U{=}2$ with results presented in Fig. 2(b)

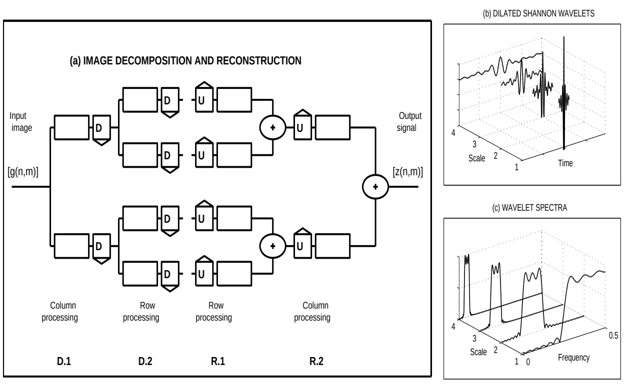

Figure 3: Image analysis by the DWT presenting **(a)** the decomposition tree with image processed by columns and rows, **(b)** the set of dilated Shannon wavelet functions, and **(c)** associated compressed spectra corresponding to dilated wavelet functions

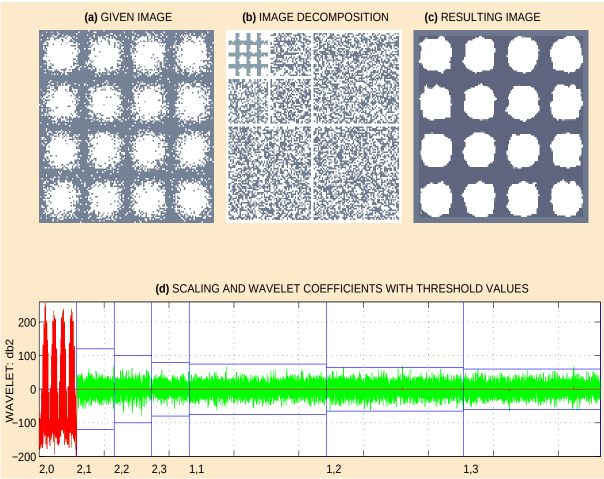

Figure 4: Principle of wavelet denoising presenting **(a)** simulated noisy image, **(b)** its wavelet decomposition into the second level by the DB2 functions, **(c)** resulting image obtained from **(d)** DWT coefficients after their local thresholding different in each decomposition level

3. image de-noising using image decomposition and the following modification of image coefficients for given threshold limits [13] and sample results presented in Fig. 4
4. interpolation of corrupted image regions [3]
5. extraction of subimage bodies using statistical properties of wavelet coefficients for selected decomposition functions and a selected level [15]

Fig. 3(a) presents the decomposition and reconstruction tree for image decomposition into the first level allowing to decompose the low-low subimage again. The decomposition function can be chosen according to the given application. Figs 3(b) and 3(c) show the set of Shannon wavelet functions in the time and frequency domains presenting changes of their resolution.

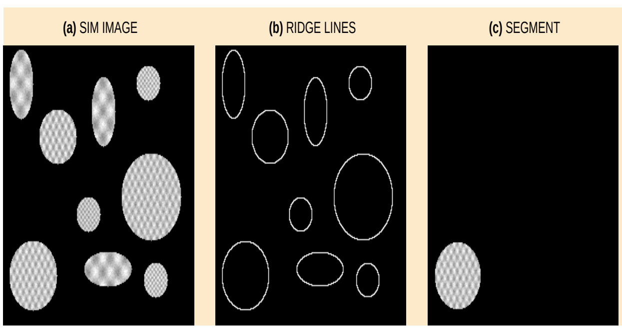

Figure 5: Image segmentation presenting **(a)** an image with simulated structures, **(b)** their watershed segmentation, and **(c)** selected image segment area

3 Image Segmentation

Image segmentation is a very common problem in many biomedical applications allowing detection of image or volume components, evaluation of their properties and the time evolution study. Fig. 5(a) presents an example of the simulated image composed of regions with different shapes and textures.

Image segmentation [8] can be based upon the watershed transform and the proposed method for classification of image segments consists of the following steps

- thresholding of image pixels to transform the image to the black and white form
- application of the distance and watershed transforms and evaluation of ridge lines (Fig. 5(b))
- detection of boundary values of individual segments and their textures (Fig. 5(c)) to define the pattern matrix for their classification

Further possibilities include the application of the region growing method for image components segmentation. In all cases it is necessary to solve problems of (i) oversegmentation [8, 21], (ii) overlapping objects, and (iii) their separation.

Fig. 6 presents selected results of segmentation of real orthodontic objects with false components obtained after the initial segmentation removed in the next step completing edges in the overlapping region.

4 Feature Matrix Estimation

Fig. 7 presents the principle of image segmentation to evaluate image components properties and to define feature vectors for each image segment. Pattern matrix formed by feature column vectors is then used for image segments classification. Different ways of image subregions feature extraction [15] include possibilities to analyze contour signals properties used in this study. The proposed method includes

- detection of image boundary and its inner texture for each image segment

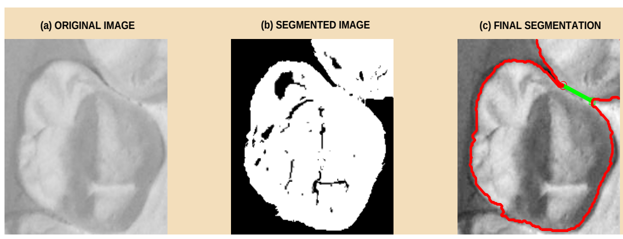

Figure 6: Segmentation of the orthodontic object with overlapping presenting **(a)** original image, **(b)** its initial segmentation, and **(c)** its final segmentation with added line for object separation

- analysis of the edge signal for each image segment and evaluation of its statistical properties
- functional transform of the edge signal or segment texture using translation independent methods to detect signal features

Both discrete wavelet transform and discrete Fourier transform have been used for signal features detection. Coefficients obtained after selected functional transforms have been used to define feature vectors including the distribution of energy and statistical properties of coefficients in the transform domain. Discrete wavelet transform proved in general its flexibility allowing to use different wavelet functions and selected decomposition levels.

The DFT and the DWT have been applied both to the boundary values of the selected object and its inner area pixels as presented in Fig. 7(c) and 7(d) for the simulated structure. Fig. 8 presents the application of the discrete wavelet transform to the edge analysis of each image segment selected in Fig. 5(c) allowing statistical analysis of resulting coefficients and feature matrix selection. Further problems include rotation-invariant texture analysis [12], the space objects detection and their volumetric features estimation useful in many biomedical applications.

5 Feature Vectors Classification

Each region after image decomposition into Q segments can be described by R features forming columns of the pattern matrix $\mathbf{P}_{R,Q}$. Each column feature vector represents coordinates in the R-dimensional space with possible clustering into S groups. The proposed set of algorithms for classification of feature vectors is based on artificial neural

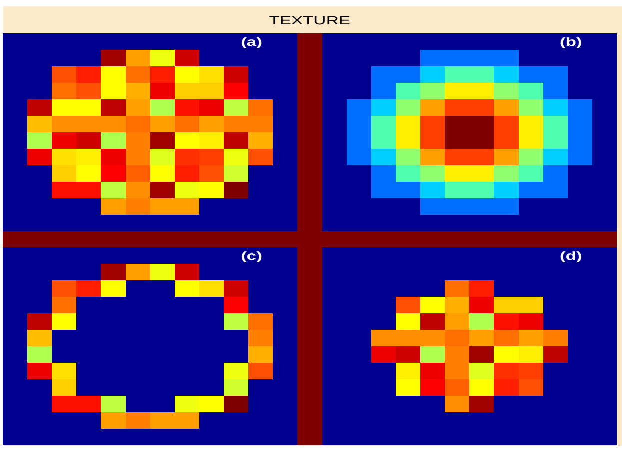

Figure 7: Principle of image segment analysis presenting **(a)** texture of the subimage object, **(b)** its distance transform, **(c)** edge values of the subimage object, and **(d)** its inner area pixels

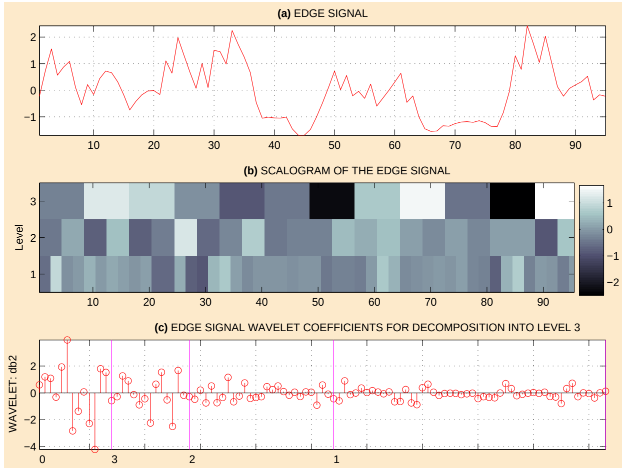

Figure 8: Discrete wavelet transform analysis applied to a selected image segment presenting **(a)** the edge signal, **(b)** the scalogram of wavelet coefficients evaluated after the signal decomposition into the third level and the DB2 wavelet function, and **(c)** discrete wavelet transform decomposition coefficients

networks [10, 18, 14] modified for the automatic selection of number of classes using the self-organized structure [6]. The learning process includes the optimization of neural network coefficients minimizing distances of the winning neuron weights and corresponding column feature vector. Final values of output neurons coefficients point to typical class elements.

Classification of Q image components with feature matrix $\mathbf{P}_{R,Q}$ formed by feature column vectors $[\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_Q]$ has been analyzed for sets with different number of features R and visualized for $R = 2$ features and S classes. To compare results for different features a specific criterion has been designed. The mean distance of each column vector $\mathbf{p}_{j_k}$ of a class segment j_k from the $i-$th class centre in the $i-$th row of matrix $\mathbf{W}_{S,R} = [\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_S]'$ can be evaluated by relation

$$MD(i) = \frac{1}{N_i} \sum_{k=1}^{N_i} dist(\mathbf{p}_{j_k}, \mathbf{w}_i) \qquad (6)$$

for $i = 1, 2, \cdots, S$ and $k = 1, 2, \cdots, N_i$ where the value N_i stands for the number of segments of class i and function $dist$ evaluates the Euclidean distance between given vectors. The proposed Cluster Segmentation Criterion (CSC) defined by relation

$$CSC{=}mean(MD)/mean(dist(\mathbf{W}, \mathbf{W}')) \qquad (7)$$

relates the mean value of average class distances to the mean value of class centers distances at the end of the learning process and it results in low values for compact clusters.

Table 1: MEAN CLASS DISTANCES OF IMAGE COMPONENTS CLASSIFIED INTO 3 CLASSES USING THE DFT AND DWT DB2 FEATURE VECTORS EVALUATED FROM IMAGE EDGE SIGNALS

Feature	*Class Distances / Typical Element*		
	Class A	*Class B*	*Class C*
(i) DFT	0.003 / 2	0.006 / 4	0.012 / 9
(ii) DWT	0.002 / 3	0.001 / 6	0.007 / 8

6 Results

Fig. 9 presents processing of feature vectors associated with the simulated image presented in Fig. 5(a) and obtained in the different way using neural networks for their classification. The proposed algorithm is able to visualize projections in case of more then two features. Fig. 9 presents the distribution of two features and their classification into three classes. Weight coefficients of the output neurons stand for typical class features at the end of the learning procedure and they represent gravity centers of individual classes. The set algorithms is able to visualize class boundaries as well and to choose typical class elements close to class centers.

Results of classification presented in Fig. 9 are compared in Table 1 summarizing the mean class distances evaluated for individual classes. Features of image edge signals have been estimated (i) by the DFT as means and variances of its coefficients in selected frequency regions and (ii) variances of the DWT coefficients using Daubechies wavelet functions of the second order and decomposition into the first and the second level. Table 1 presents indices of typical image object elements with the lowest distance of its feature vector elements from the neuron weights detecting the same class as well.

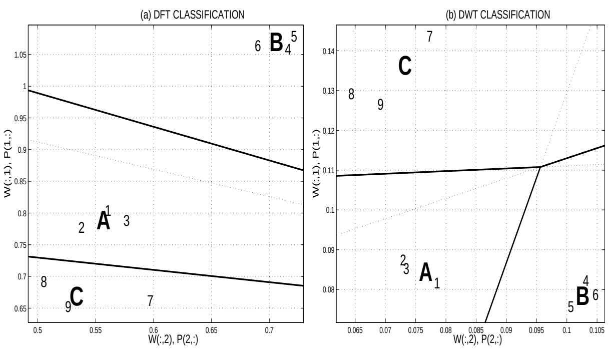

Figure 9: Distribution of feature values evaluated from edge signals of simulated image components using **(a)** the DFT and **(b)** the DWT, classification of feature vectors into 3 classes and visualization of typical features and boundaries of individual classes

The proposed algorithm of object segmentation, feature vectors definition and their classification has been used for analysis of selected biomedical images. Fig. 10(a) presents an example of the selected brain image after its de-noising to reduce problems of oversegmentation and after its resolution enhancement. The whole algorithm includes (a) image preprocessing, (b) detection of subimage edges, and (c) extraction of the vein in the image. The next steps include (d) the detection of edge signal, (e) its 2D visualization, and (f) its analysis either by the DFT or DWT to find its feature vector used for their classification.

Both watershed and region growing methods can be used to detect image segments in selected applications. In case of real signal processing it is necessary to choose appropriate preprocessing methods to reduce problems of oversegmentation and detection of overlapping objects. The appropriate segmentation allows the following efficient feature extraction.

7 Conclusion

The paper is devoted to specific topics and problems of biomedical image segmentation and classification using wavelet transforms. A special attention is paid to image enhancement and denoising by image wavelet decomposition and reconstruction followed by segmentation of image components and the use of functional transforms to estimate image feature vectors. The final part of the work is devoted to classification of image objects using the pattern matrix. The proposed criterion has been used to compare results of clustering by the FFT and DWT for feature

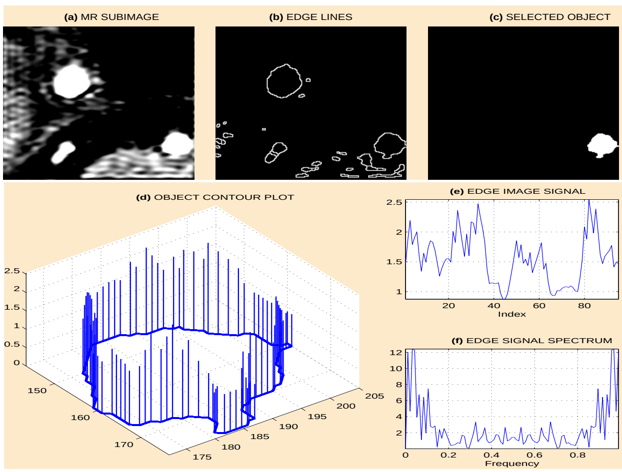

Figure 10: Analysis of a selected part of the brain MR image presenting **(a)** given MR subimage, **(b)** edges of individual image structures, **(c)** an image object standing for a vein, **(d)** the edge signal of the vein in the 3D space, **(e)** the edge signal, and **(f)** the DFT of the edge signal used for estimation of object features

vectors definition with better results obtained for the wavelet transform owing to its flexibility and possibility to choose different wavelet functions.

Proposed algorithms of image components segmentation and classification form a library allowing to use artificial neural networks for (i) classification of feature vectors, (ii) suggestion of the number of classes with visualization of class boundaries, and (iii) the choice of typical image segments. Methods presented have been used for analysis of shapes of biomedical images with application in neurology and detection of specific objects in the brain.

The future work will be devoted to further biomedical applications including research related to orthodontic images [21, 11] and lung granuloma study with emphasis to segmentation of overlapping objects. A specific research will be devoted to their three-dimensional modelling, visualization and study to contribute to problems of early diagnostics of serious diseases.

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