Texture Segmentation and Classification in Biomedical Image Processing

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Abstracts: *Methods of image analysis belong to a general interdisciplinary area of multidimensional signal processing. The paper is devoted to selected intelligent techniques of biomedical image processing and namely to mathematical methods of image features extraction and image components classification invariant to their rotation. The first method under study presents an algorithm for the given image segmentation using watershed transform allowing the estimation of image segments boundaries and image components classification. This problem is studied in connection with the application of the Radon transform used to change texture rotation to its translation followed by the shift invariant wavelet transform to estimate image components features. The second method presents basic principle of feature based image segmentation using pattern vectors assigned to all image pixels with vector values estimated from each root pixel neighbourhood properties. Proposed methods are verified for simulated images formed by a mixture of different textures and then applied to selected biomedical images.*

Keywords: Image segmentation, watershed transform, feature extraction, Radon transform, wavelet transform, classification, neural networks, biomedical image processing

1 Introduction

Image components classification forms a basic problem in many areas including applications in biomedicine, environmental image processing, engineering etc. The fundamental problem is in image segmentation followed by image segments feature extraction invariant to image texture rotation, translation, scaling and illumination. Associated mathematical methods studied in the paper cover (i) the use of Radon (RT) and wavelet transforms (WT) to define image components properties [4, 7, 10, 13, 14] and (ii) the application of clustering algorithms for these pattern values including neural networks [6] use.

A different approach to image analysis is based upon the selection of appropriate features assigned to all individual image pixels. Values of a feature vector associated with each image pixel are evaluated from the root pixel neighbourhood of the selected shape and size [11]. Image pixels can then be classified directly into the given number of levels in the case of the properly chosen set of feature vectors.

The following study presents fundamental methods of image segmentation by the watershed transform and the following feature extraction using Radon and wavelet transforms at first. This approach to image classification is then compared with that using feature based image segmentation by feature vector values associated with each image pixel. Proposed methods have been verified for simulated structures and then used for processing of real biomedical images acquired by the magnetic resonance (MR) method. Resulting algorithms have been designed in the MATLAB environment.

2 Image Components Detection

A watershed segmentation [5] used for image components detection is based on the geographical meaning of this word and it forms a fundamental mathematical tool for the gray-scale image segmentation [1]. The principle of this method assumes the initial change of the given image into another one whose catchment basins are the objects or regions we want to identify and to find their contours. The proposed algorithm consists of these steps

- image de-noising and thresholding for its conversion into the black and white form
- distance and watershed transform use to find watershed regions identified by a labelled matrix with its positive integer elements standing for watershed regions and zero elements defining image components contours
- extraction of individual image components, their boundary signals and textures

Proposed methods of image segmentation have been applied to a biomedical MR image of the brain with results presented in Fig. 1. A selected image component in Fig. 1(c) represents one of veins that can be further used as an object for classification.

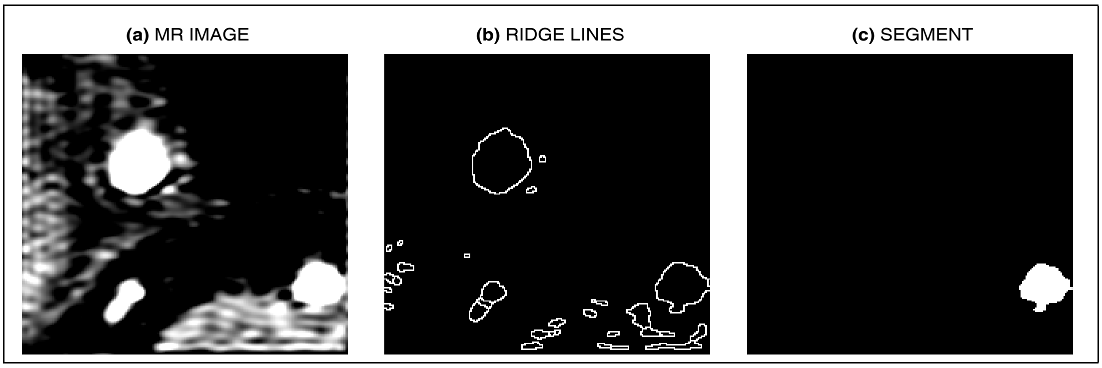

Figure 1: An example of MR image segmentation presenting **(a)** original MR area, **(b)** ridge lines resulting from its distance transform and watershed segmentation, and **(c)** a selected segment

The watershed transform is able to detect most of image components even though the problem of fault class boundaries can arise in some cases. The proper segmentation is the fundamental task for further image analysis.

The process of image components classification assumes the definition of the pattern matrix containing their features. Many possibilities of feature extraction [9] include

- analysis of statistical properties of the signal on the image component boundary or analysis of the whole component structure
- transform of boundary signal or component structure using methods defining features independent to image component translation or rotation

Self-organizing neural networks can be then used to recognize groups of similar input vectors in the pattern matrix and to classify image components.

3 Radon and Wavelet Transforms in Features Extraction

Estimation of image features using Radon and wavelet transforms [10] allows the efficient classification of image components independent to their rotation. The Radon transform (RT) of a two-dimensional function $f(x, y)$ introduced in 1917 as a collection of one-dimensional projections [2] of a body to planes rotating round an object at angle intervals Θ is defined as

$$R(\Theta, r)[f(x, y)] = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x, y)\ \delta(r - x\cos\Theta - y\sin\Theta)\ dx\ dy \tag{1}$$

where r is the perpendicular distance of a line from the origin and Θ is the angle of rotation. It is possible to analyse this relation taking into account that the value of δ function is nonzero for its argument equal to zero only which defines the set of parallel lines

$$y = -x \ \cot\Theta + r/\sin\Theta \tag{2}$$

for a constant value of Θ and parameter r used for integration of the given image. The plane (x, y) is transformed in this way to the plane (Θ, r) according to Fig. 2 changing rotation in the original space to its translation along parameter Θ in the RT space.

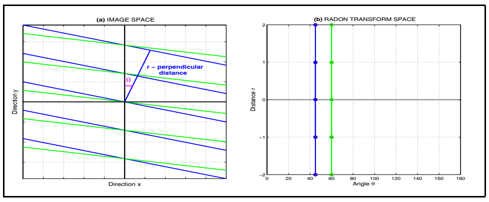

Figure 2: RT principle presenting **(a)** the set of parallel integration lines and **(b)** corresponding RT space

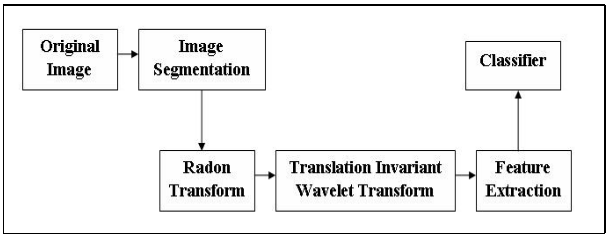

Figure 3: Block diagram of the proposed technique of image segmentation and classification

The discrete Radon transform called Hough transform has been introduced in 1972 by R. Duda and P. Hart with its inverse form used as the fundamental mathematical tool in computer tomography allowing the reconstruction of the two-dimensional image from its projections for the set of rotating sources of beams and rotating sensors.

The use of Radon and wavelet transforms for extraction of rotation and translation invariant image components features is presented in Fig. 3. At first all image components are identified using distance and watershed transforms. Then the Radon transform of individual image segments is evaluated followed by the translation-invariant discrete wavelet transform (DWT). Its decomposition coefficients are then used for estimation of image segment features.

Results of the use of Radon and wavelet transforms for analysis of a biomedical image are presented in Fig. 4. As the original image in Fig. 4(a) rotates its Radon transform in Fig. 4(b) is shifted. Features evaluated from wavelet transform coefficients have been then classified by neural networks. Fig. 5 presents the effect of the Radon transform application for a rotated image component to the variation of its features which is considerably decreased by this process.

Numerical results pointing to the efficiency of the proposed method are presented in Table 1 for the set of identical MR images rotated from 0 to 180 degrees by the step of 10 degrees presenting the standard deviation (STD) of image features evaluated as the sum of squared diagonal values of discrete wavelet transform coefficients after image decomposition into the second level.

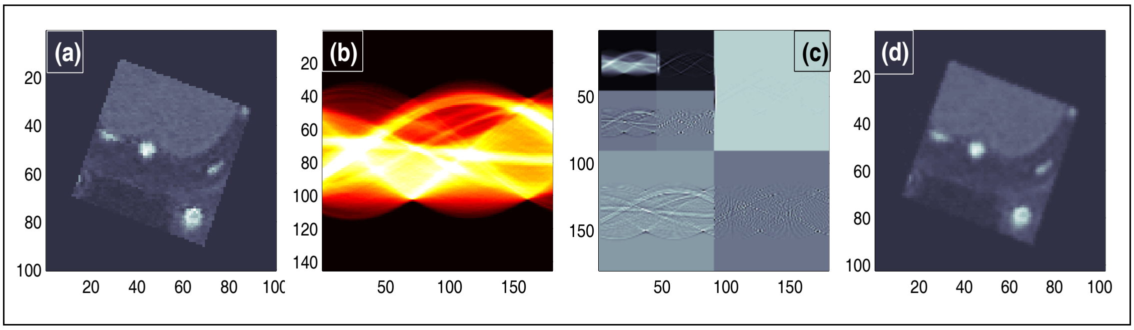

Figure 4: Processing of the MR image presenting **(a)** the original image, **(b)** its Radon transform, **(c)** the following wavelet decomposition into the second level, and **(d)** its reconstruction

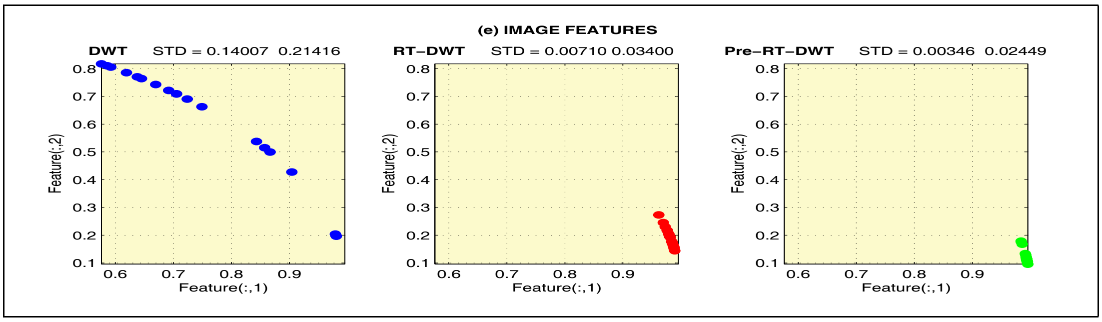

Figure 5: Variation of the MR image features estimated for the set of its rotations presenting features obtained as squared Daubechies diagonal DWT coefficients evaluated from the set of original images, original images after the RT use, and de-noised images followed by the RT

Table 1: Standard deviation of the sum of squared diagonal DWT coefficients in the first and the second decomposition levels using (i) original image, (ii) Radon transform, and (iii) de-noising before the Radon transform use

STD of MR Image Features		
Method of feature extraction	*Feature 1*	*Feature 2*
DWT	0.141	0.2142
RT - DWT	0.007	0.034
Image de-noising - RT - DWT	0.003	0.024

4 Feature Based Image Segmentation

Feature based image segmentation (FBIS) and content based image retrieval (CBIR) [11, 12] form a very efficient alternative to image segmentation. The principle if these methods is based on the construction of the feature vector associated with each image pixel evaluated from values in the boundary of each root pixel. Resulting feature matrix is then used for image classification.

The fundamental algorithm assumes processing of the intensity image defined by a given matrix **R** with its values in the range $\langle 0, 1\rangle$. Fig. 6 presents main commands for definition of the corresponding feature matrix **F** using the neighborhood of each root pixel of the square shape and given size defined by a matrix **B**. Feature values evaluated by the user defined function $Feature$ can estimate the root pixel feature in the range $I \in \langle 1, 2, \cdots, L\rangle$ for the given number of levels L using many methods including the use of

- standard deviation of pixel values in each matrix **B**
- histogram values of pixels in each matrix **B** and feature estimation based upon the most probable intensity level
- image energy values estimated from values of a matrix **B** including the WT coefficients use

```
% Feature Based Image Segmentation
% Input variables: R - Initial image
%                  L - Number of final image levels
% Output variable: F - Feature matrix
   Region = [7,7];          % Selection of the neighbourhood size defining matrix B
   FeatureValue = 'Feature';   % Function defining the root pixel feature
   F = nlfilter(R, Region, FeatureValue);    % Neighborhood image processing
```

Figure 6: Feature matrix definition using a function for each root pixel feature vector estimation

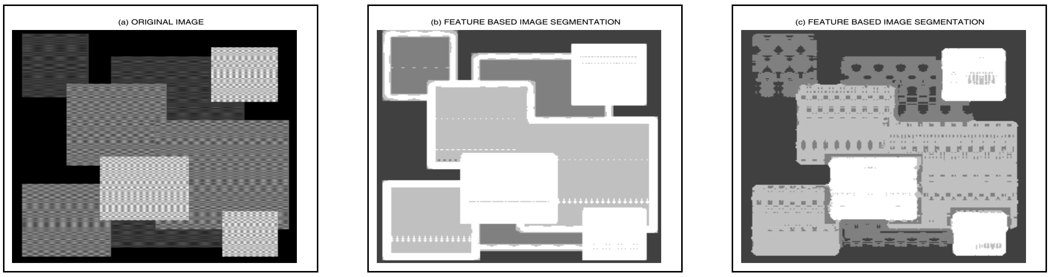

Figure 7: Feature based image segmentation presenting **(a)** original simulated image, **(b)** feature matrix evaluated through standard deviations of image pixel intensities in the neighbourhood of each root pixel, and **(c)** feature matrix estimated through histogram values

Selected results of a simulated image processing are presented in Fig. 7 for image classification into four levels. Figs 7(b) and (c) provide comparison of feature matrices obtained from the neighborhood of each root pixel using the standard deviation of their intensities and their histogram values.

Image noise and texture rotation can substantially influence results of feature vector definition in the case of feature based image segmentation as well. Owing to results in the previous chapter it is possible to recommend the use of the Radon transform in this case as well preceded by image de-noising to estimate image components features more precisely. Further methods based upon complex wavelet transform and computational inteligence has been discussed in [3, 8].

Proposed algorithms of image segmentation were verified for simulated images formed by the mixture of different textures and then applied to selected biomedical images. An application of the processing of the MR image of the backbone is presented in Fig. 8 for its segmentation into 4 levels and a selected square neighbourhood of each root pixel in this case.

5 Conclusion

The contribution is devoted to image classification methods using two different principles. The first one is based upon the watershed and distance transforms use allowing to process the image without any previous knowledge of the number of image segments. Selection of features of separate segments allows the following classification into the given number of classes using a pattern matrix and appropriate clustering methods. The second method is based upon the direct estimation of pixel features using their neighbourhood.

Figure 8: Image feature based segmentation of the MR image of the backbone presenting **(a)** original biomedical image and **(b)** its segmentation into four levels

While the first method can be very sensitive to the additive image noise and oversegmentation the second one is restricted to the preliminary knowledge of the number of image levels. But this method using feature based image segmentation is very efficient in the case of properly chosen properties defining feature vectors values associated with all image pixels.

Acknowledgments

The work has been supported by the research grant of the Faculty of Chemical Engineering of the Institute of Chemical Technology, Prague No. MSM 6046137306.

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