A HYBRID APPROACH FOR BRAIN TUMOR DETECTION IN MRI IMAGES

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Abstract

In this paper we present a hybrid approach based on texture analysis and active contour segmentation for the 3 grades of meningiomas. Since the shape of the tumors plays a major role in its classification, we propose to segment the area of the meningioma on the base of the active contour without edges. We use the second-order texture analysis through Gray-Level Co-occurrence Matrices to extract and analyse some texture features, such as contrast, correlation, homogeneity, energy and entropy. The experiments, performed in MATLAB environment with real MRI images of a human brain have shown good results for detection of meningioma in the diagnostic phase, which can help for successfully treatment of this disease.

1. INTRODUCTION

Meningiomas are the most common type of primary brain tumors, which present approximately of 30 % of all brain tumors. It arises from the meninges, the outer three layers of protective tissue located between the skull and the brain [1, 2]. Meningioma can be graded in 3 grads, based on the appearance of the tumor cells under a microscope. Grade I is the most common type of meningioma, it grows slowly and is considered benign. Grad II (atypical meningioma) grows more quickly. Grade III (anaplastic/malignant meningioma) grows and spreads quickly. It is the most aggressive form and is considered malignant [1]. Magnetic resonance imaging (MRI) is preferred technology to diagnose meningioma because it can create more detailed images than CT scans and often shows changes in the brain caused by the tumor, such as swelling or areas where the tumor has grown [3]. Meningiomas are characterized in the MR image by a relatively smooth, regularly appearing border. In many cases the segmentation of brain tumors is a complex task due to tumor shape, size and location that vary greatly across different patients [4, 5]. The presence of noise of different nature in many cases complicates accurate diagnosis [6].

Many methods and approaches have been proposed for detection and classification of different brain tumors in MR images, particularly, fuzzy clustering means (FCM), support vector machine (SVM), artificial neural network (ANN), Deep Learning model (DLM) and expectation-maximization (EM) algorithm technique [7,8,9]. Some of the popular techniques for extracting the important information from images are based on region growing based segmentation [10]. The features extraction approaches can obtain texture characteristics on the base on Local Standard Descriptor (LBP), Grey-Level Co-occurrence Matrices (GLCM) or their modifications [11].

We propose a hybrid approach based on active contour segmentation and texture features analysis to detect the 3 grades of meningioma in MRI images.

The rest of the paper is organized as follows. In section 2, we present the basic stages of the proposed approach. Some results, obtained by the simulation and discussion are introduced in section 3. Finally, conclusion is given in section 4.

2. MAIN STAGES OF PROPOSED APPROACH

The proposed hybrid approach consists of the following main stages:

- Pre-processing
- Meningioma segmentation via active contour and calculation of tumor area
- Texture analysis based on GLCM

2.1. Pre-processing

The complex effect of the influence of some different artefacts in MR images can be presented as kind of noise. MR images are mostly corrupted by Rician noise, which arises from complex Gaussian noise in the original frequency domain measurements [12]. We propose to reduce this noise based on the homomorphic wavelet filter due to the best SNR results for MRI images [6].

2.2. Meningioma segmentation

We propose to apply the active contour model of Chan and Vese for segmentation in individual MR images, as well as in the entire MRI sequence. This model guarantees greater smoothness of the contour and accuracy of segmentation compared to the other known ones. The algorithm for determining the initialization contour (mask) from which the segmentation begins will be the same. But in segmenting the entire sequence, this algorithm will be applied to the image in which the tumor is best seen. From this image we can get a more accurate initial contour for segmentation.

The model is a special case of the Mumford–Shah function. Mumford and Shah approximate the image f by a piecewise-smooth function u as the solution of the minimization problem. Compared to the piecewise constant Mumford - Shah model, the key differences with the Chan - Vese model are an additional term penalizing the enclosed area and a further simplification that u is allowed to have only two values, $c1$, $c2$ are the values of u respectively inside and outside of the boundary of a closed set C [13].

The main idea is to find among all u of this from the one that best approximates f [14]. Now is needed minimization over all set boundaries C. This is made by applying the level set technique introduced by Osher and Sethian, where is used a level set function φ for a circle of radius r. The Dirac function δ, which is the gradient of the Heaviside function, penalizes long boundaries between the regions [14].

The flowchart of the main algorithm for tumor segmentation in the MRI sequence is shown in Fig. 1.

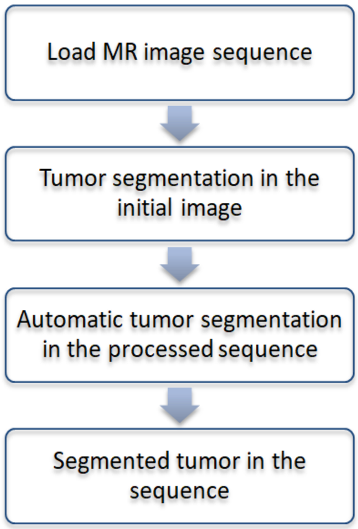


Figure 1. Flowchart of main algorithm for segmentation

For solving this task and to make the initial segmentation of the primary image we choose the following specific parameters for the segmentation [15]:

- *mask* – Initial contour at which the evolution of the segmentation begins;
- *n* – Maximum number of iterations to perform in evolution of the segmentation;
- *R* – Radius of the location in pixels;
- *Alpha* – 'Smooth Factor' — Degree of smoothness or regularity of the boundaries of the segmented regions;

The flowchart of algorithm for creating the initial contour (mask) is given in Fig. 2.

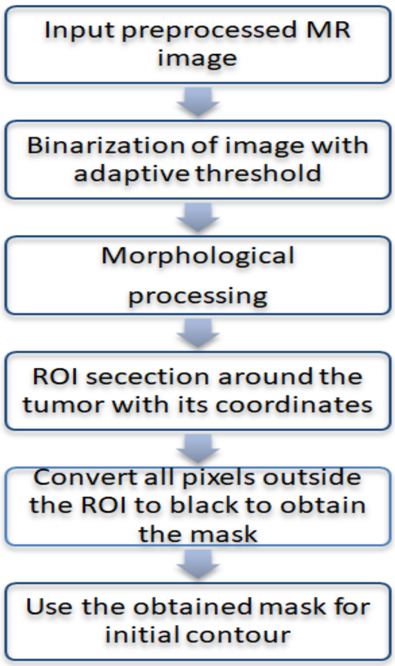


Figure 2. Flowchart of algorithm for creating the initial contour

For binarization the method of Otzu was proposed. After that we use morphological oppening to remove all small objects around the tumor and preserve its shape and size. We choose a disk structure element, therefore, the tumor usually is oval and in determining the correct width, the square ROI can keep the shape of the tumor. Next, the initial contour is obtained. Finally, the segmentation via active contour without edges in the MR image is made. Using this algorithm, we can successfully segment the tumor into single images.

Once the image in which the tumor is best seen has been selected, we propose to segment the sequence in two directions (forward and backward from the original image) to segment all the images in the sequence. That means we can build two loops: one incrementing and other decrementing to craw the array of images with tumor in the sequence. This approach is appropriate, because in the most cases the tumor is getting smaller in these two directions in the sequence. Each subsequent image uses as mask for its segmentation with active contours without edges the result of the segmentation of the previous image [16]. Each image is processed primarily as described above. The segmented meningioma is visualized with yellow contour on the preprocessed images. Finally, the area covered by the tumor can be calculated in pixels using the area of the resulting contour mask.

2.3. Texture analysis based on GLCM

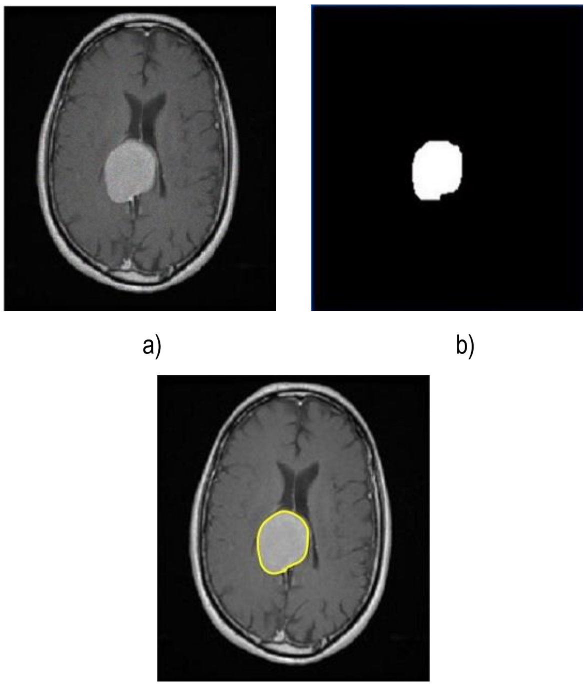
The second-order statistical method that takes into account the spatial relationship of pixels in an image is the Gray-Level Co-Occurrence Matrix (GLCM), also known as the Gray-Level Spatial Dependence Matrix. The functions of the GLCM characterize the texture of the image by calculating how often pairs of pixels with a specific value and in a specific spatial relationship appear in an image. In this way a GLCM is formed and statistical measurements are taken from it [17]. The representation of the image texture is contained in the co-occurrence matrices calculated in four directions, namely, 0^0, 45^0, 90^0, and 135^0. We can extract information about the structure from the examined texture by using texture properties. Fourteen local properties have been suggested by Heralick et al. for this purpose [18].

In our study, we have used some textural characteristics as the most useful such as contrast, correlation, homogeneity, energy, and entropy. Analyzing these texture characteristics, we can conclude about their behavior in the three different grades of meningioma, which is very useful for their early detection.

3. RESULTS AND DISCUSSION

The experiments were performed in MATLAB 9.7 environment. Thirty real digital MRI – T1 images in axial plane of a human brain with the 3 different grades meningioma (10 from each grad) are used for the experiments. The images are from database of Radiopedia [19]. We have used also 3 MRI series of the brain with size 256x256 pixels from the database of Medical University of Sofia.

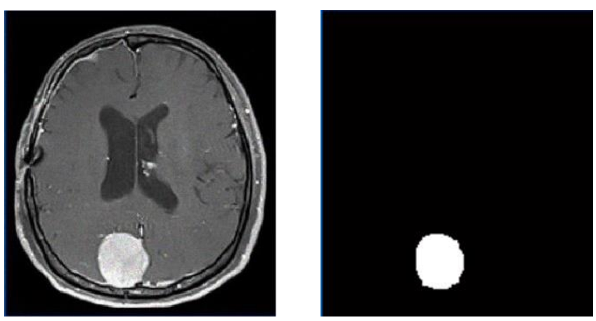
Some results from our experiment are given in the next figures below. They show the results from segmentation of meningioma in the 3 grades from single MR images.



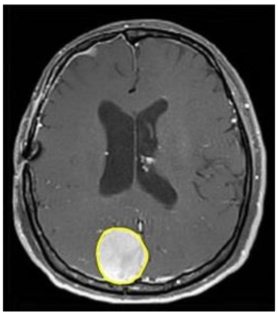
a) b)

c)

Figure 3. MRI image of meningioma grad I:
a) original; b) mask for initial contour
c) segmented image with tumor area 2337 pixels

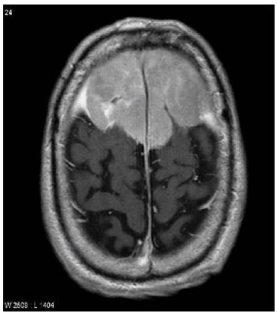


a) b)

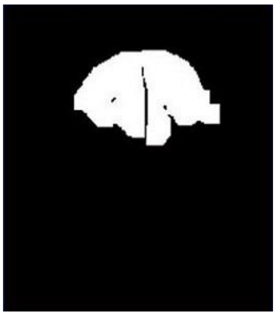


c)

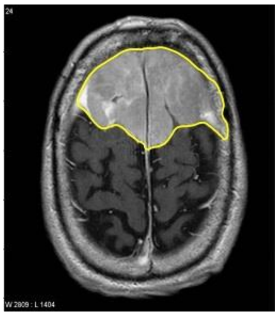
Figure 4. MRI image of meningioma grad II: a) original; b) mask for initial contour c) segmented image with tumor area 2089 pixels



a)



b)



c)

Figure 5. MRI image of meningioma grad III:
a) original; b) mask for initial contour
c) segmented image with tumor area 7977 pixels

The segmented images are obtained by following specific parameters: n=50, R=10 pixels, smooth factor *alpha*=2.

Some average results of the texture characteristics obtained for the 3 grades of meningioma, are presented in the following tables.

Table 1. Contrast

Angle	Meningioma grad I	Meningioma grad II	Meningioma grad III
0°	0.08	0.1	0.13
45°	0.12	0.18	0.17
90°	0.06	0.12	0.1
135°	0.13	0.17	0.175

Table 2. Correlation

Angle	Meningioma grad I	Meningioma grad II	Meningioma grad III
0°	0.99	0.984	0.987
45°	0.985	0.971	0.984
90°	0.992	0.983	0.992
135°	0.985	0.972	0.984

Table 3. Homogeneity

Angle	Meningioma grad I	Meningioma grad II	Meningioma grad III
0°	0.968	0.96	0.958
45°	0.959	0.948	0.942
90°	0.971	0.96	0.96
135°	0.958	0.947	0.943

Table 4. Energy

Angle	Meningioma grad I	Meningioma grad II	Meningioma grad III
0°	0.28	0.27	0.23
45°	0.27	0.255	0.225
90°	0.28	0.27	0.235
135°	0.27	0.255	0.225

The obtained average results for the entropy are as follows: for grad I is 5.783, for grad II is 6.355 and for grad III is 8.583. This shows that when the difference between the maximum and minimum image intensity is very small, which characterizes cases with a low grades of meningioma, the image has low entropy and low contrast.

The corresponding graphical representation of these characteristics is given in Figure 6, Figure 7, Figure 8 and Figure 9.

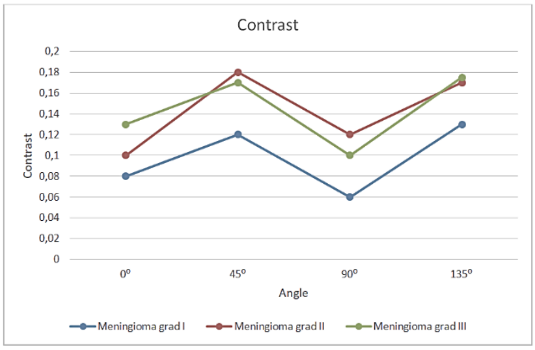


Figure 6. Contrast for the 3 grades of meningioma

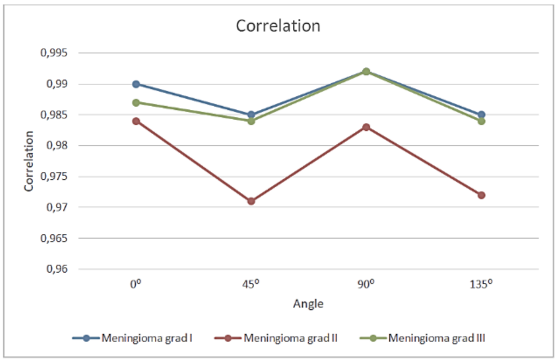


Figure 7. Correlation for the 3 grades of meningioma

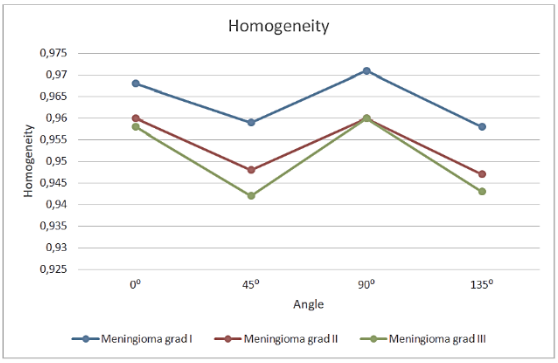


Figure 8. Homogeneity for the 3 grades of meningioma

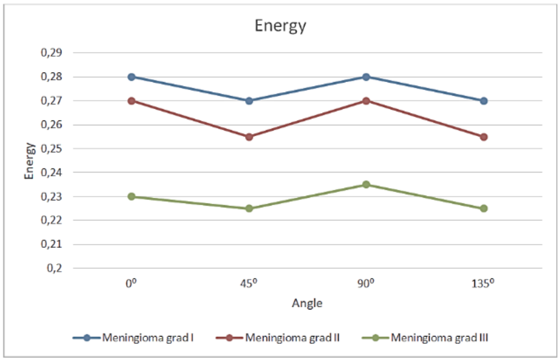


Figure 9. Energy for the 3 grades of meningioma

The obtained results of correlation show how the gray values of the pixel pairs change. If the values are higher than zero, it means that the pixel pairs have roughly similar gray values. All values here are very close to 1, from which it can be determined that there are no dramatic changes in the gray values, but there is a fairly smooth gradient of gray values. But we can find the peaks at the 0^0 and 90^0 angles. This shows that the different gray values gently overflow in these directions. The situation is similar with the homogeneity. If we now look at the images, it is clear that several textures can be distinguished on the images of the meningioma of grade III. Grade I meningioma are characterized by high homogeneity of cell structure. The energy values show that despite being close, the highest energy is in grade I and the lowest in grade III. This is due to the lower homogeneity in the cell structure of the tumor.

4. CONCLUSION

In this paper we present a hybrid approach based on active contour segmentation and texture features analysis to detect the 3 grades of meningioma in MRI images. Our hybrid approach shows the highest Dice coefficient (DSC) for segmenting the tumor (96.2%) in the single images. This is better compared to the active contours without edges (94.5%) and a growing region, or compared to the approach presented in [4], where the Dice coefficient is 90%. It offers the opportunity to detect the different grades of meningioma, not just the classification of grad I and anaplastic. In many clinical cases, the degree is determined only by the area of the tumor, but our study has shown that the application of textural characteristics is crucial in this classification.

Our future work will be related to conducting more experiments in terms of research for series of images, not only in axial plane, as well as combining the proposed approach with other methods such as DLM for automatic classification of the individual grades of meningioma.

5. ACKNOWLEDGMENTS

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