Segmentation of Brain Tumors from Magnetic Resonance Images using Adaptive Thresholding and Graph Cut Algorithm.

Zuzana Bobotová*
Supervised by: Ing. Wanda Benešová, PhD.†

Institute of Applied Informatics
Faculty of Informatics and Information Technologies
Slovak University of Technology
Bratislava / Slovakia

Abstract

Development of methods for automatic brain tumor segmentation remains one of the most challenging tasks in processing of medical data. Exact segmentation could improve the diagnostics, as for example the time evaluation of the tumor volume. However, manual segmentation in magnetic resonance data is a time-consuming task. We present a method of automatic tumor segmentation in magnetic resonance images which consists of several steps. In the first step, a high intense cranium is removed from the image. In the next step, the histogram parameters of the image are analyzed using the method *Mixture of Gaussians*. These parameters control the morphological reconstruction (proposed by Luc Vincent 1993). The morphological reconstruction is followed by substraction and thresholding. It produces a binary mask which is used in the last step of the segmentation: graph cut segmentation. First results of this method are presented in this paper.

Keywords: segmentation, brain tumor, Magnetic Resonance Imaging, morphological reconstruction, adaptive thresholding, graph cut algorithm, Mixture of Gaussians

1 Introduction

Medicine and diagnostics work with a large amount of visual data. Computer vision methods and image processing can help doctors with analysis. Hence, the doctors save their time and can focus on other important tasks.

Medical examination includes tests like MRI - Magnetic Resonance Imaging, CT - Computed Tomography, PET - Positron Emission Tomography, X-ray scans and other less known techniques. Test results can be represented by a single scan or by series of images. Then doctors analyze images and search for anomalies, damages or symptoms of the disease. The goal of the research is to replace a manual or semi-automatic analysis by the automatic processing using methods of computer vision. Nowadays, computer vision segmentation methods are used in the analysis of subset of cells, organs or whole systems from the scans.

The aim of our work is to find an appropriate automatic method to segment brain tumors from magnetic resonance images (MRI). Output of a 3D MRI scan is a sequence of images called slices. These MRI data are stored in special medical formats such as *NIFTI* or *MHA*. Our goal is to segment the tumor from the 2D image (one slice) automatically. The presumption of the proposed method is that in the processed image of the brain is a tumor is included.

It is a very interesting area of research, because it is necessary to solve several problems. MR images are scanned with different contrasts characteristics. In addition to tissue density, tissue relaxation properties contribute to image contrast in MR images. Basic relaxations are T1 and T2. Next challenge is to deal with different sizes, shapes and intensity levels of tumors on the images. Intensity levels of the tumor depend on the aggressiveness of the tumor. Aggressive tumors are less intensive and they can blend with other brain material. The edges of such tumors are not clear.

2 Related works

Many computer vision segmentation methods have been developed during the last years. The article by Gordillo et al. [2] and also the article by Liu et al. [5] list the most suitable methods for medical imaging and brain tumor segmentation: global and local thresholding, region-based methods such as region-growing and watershed algorithm, pixel classification methods and clustering such as Fuzzy C-Means, k-means, Markov Random Fields, Bayes method and Artificial Neural Networks. Some algorithms implement these methods with various types of improvements.

Menzein et al. presented article [7] about Multimodal Brain Tumor Image Segmentation Benchmark (BRATS). Twenty tumor segmentation algorithms were applied to a set of 65 multi-contrast MR images. In the research were implemented several segmentation methods and most of them were automatic. All methods were tested on the

*bobotova.zuzanka@gmail.com
†benesova@fiit.stuba.sk

same dataset. Results of their tests show that different algorithms worked best for different sub-regions. Successes of methods ranged between 74% and 85%. They found that no single method performed best for all regions.

Khotanolou et al. presented automatic segmentation algorithm [4] to detect brain tumor in 3D MRI data. In first phase, initial tumor segment is detected using histogram analysis, morphological operations and symmetry analysis. Then the tumor is detected using fuzzy classification and symmetry analysis again. Their results show that method is effective and suitable for brain tumor detection.

Prastawa et al. presented framework [9] for automatic brain tumor segmentation based on outlier detection. At first, abnormalities were detected using information about intensities. Secondary, tumor and edema presence is verified. Finally the spatial and geometric properties are used for determining proper sample locations. Method was tested on three datasets.

Havaei et al. presented article [3] about brain tumor segmentation method last year. They implemented deep neural networks with two different types of architectures. First type was two pathway architecture made from two streams. It allowed follow two aspects - visual details of the region around that pixel and where the patch is in the brain. Secondary three types of cascade architecture were implemented. Results of the methods are very promising.

Another work [8] from the last year published Prajapati and Jadhav. They utilized the following steps in their method for brain tumor segmentation from MR images: morphological operations, thresholding and region growing segmentation. Results of their tests show that region growing method is suitable for brain tumor detection.

3 Algorithm overview

MR images in our dataset differ in the space resolution and also in the intensity resolution. Hence, tumor segmentation must reckon with several problems. Intensities of tumors on the images are different according to tumor aggressiveness. Tumors have various shapes and localization and vary in sizes. Bigger tumors are not problematic for segmentation, but some tumors are very small and their intensities, sizes and shapes are very similar to other healthy brain parts. In our research, we develop an automatic method to solve the problems listed above.

The method consists of three steps as shown in Figure 1. First, the contrast is enhanced by image rescaling. In the second step, the cranium (skull) should be removed from the image. It means bones around the brain mass which protect the brain. The removing of cranium is important for the further processing, mainly in cases when it is of high intensity. In fact, the segmentation of a tumor could be confused by cranium, because a tumor has high intensity too. The final step is the tumor segmentation. The result is MR image with indicated boundaries of the tumor counted by two different algorithms.

Figure 1: Steps of algorithm

4 Used methods

Several well-known computer vision methods are used in the proposed algorithm: *Mixture of Gaussians*, morphological operations and greyscale morphological reconstruction, thresholding and graph cut algorithm. Chapters 4.1 – 4.5 contain general explanation of these methods and chapters 5.1 – 5.3 explain the order, the reasons and the implementation of the methods.

4.1 Mixture of Gaussians

Gaussian mixture distribution is a multivariate distribution that consists of a mixture of one or more multivariate Gaussian distribution components. The number of components is fixed as input parameter. Each multivariate Gaussian component is defined by its mean and covariance, and the mixture is defined by a vector of mixing proportions.

4.2 Morphological operations

Morphology is the study of shape. Mathematical morphology mostly deals with the mathematical theory of describing shapes using sets. In image processing, mathematical morphology is used to investigate the interaction between an image and a certain chosen structuring element using the basic operations of erosion and dilation [6].

In our work, we use basic operations like open and close as well as more advanced morphological operation. Morphological reconstruction described in the next paragraph.

4.3 Greyscale morphological reconstruction

Greyscale morphological reconstruction is an iterative process. Input for the algorithm is mask image. Actually mask image is the processed image. Algorithm also needs marker image as shown in Figure 2. Greyscale morphological reconstruction is described in detail in the book by Šikudová et al. [12].

In basic morphological reconstruction binary dilation or erosion is applied for the marker image. Then the algorithm calculates the intersection with mask image. The processing continues until the mask image values stop changing.

Greyscale morphological reconstruction is based on similar principles. However, binary dilation or erosion is replaced with greyscale dilation or erosion and intersection is replaced with the selection of the minimum value among the sets of points.

Method is usually used for removing local maximas of the image. However, it is important to extract loacal maximas not remove them in some cases. Hence, reconstructed image is substracted from the input image as shown in Figure 2.

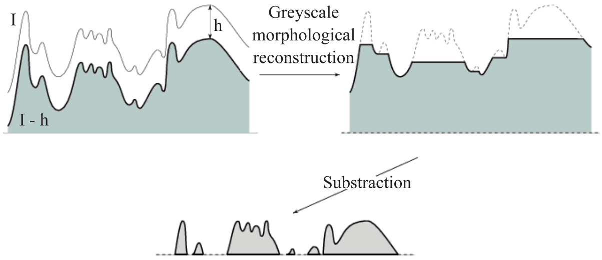

Figure 2: Greyscale morphological reconstruction followed by substraction [12].

4.4 Thresholding

Thresholding is one of the simplest segmentation methods. Basic method exchanges each pixel $P_{i,j}$ in the image for black or white pixel according to intensity I of the pixel [11]. Thresholding input value is fixed constant called threshold. If $P'_{i,j}$ is thresholded version of $P_{i,j}$ according to intensity $I(P_{i,j})$ and T is threshold then:

$$P'_{i,j} = \begin{cases} 1 & if \quad I(P_{i,j}) >= T \\ 0 & otherwice \end{cases}$$

In the medicine, segmentation by thresholding often fails, because medical images have very complex distribution of intensities [1]. However, thresholding methods are often followed by other segmentation methods or combined with other methods. Threshold in our method has been derived using *Mixture of Gaussians* method.

4.5 Graph cut segmentation

Graph partitioning methods are efficient for the segmentation. They model the image like a weighted graph as explained in [13]. In this algorithm pixels are associated with nodes. Connections between them create weighted edges. Values of the weights depend on similarities or dissimilarities between neighboring pixels. The graph cut is a way how to partition one graph into two regions according to some characteristics. Edges created between two partitions of the graph are called cut edges. They have weights depending on the weight values of edges between pixels. Resulting weight of the cut is the sum of the weights of the cut edges. Finally, the result is a set of partitions and every partition is a segment of the image.

There are many partitioning methods. One of them is *GrabCut* algorithm from OpenCV library. It was designed by Rother et al. and described in the article [10].

Originally the algorithm needs user interaction to draw the input rectangle around the foreground region. The algorithm iteratively segments the foreground using Gaussian Mixture Model. The resulting distribution of pixels is used to build the graph. Nodes in the graph are pixels and two next nodes are added, source node as S and sink node as T. Each pixel in the foreground is connected to the S node and each pixel in background is connected to the T node. The weights of edges which connect pixels to the S or T node are defined by the probability that a pixel is in the foreground or in the background. The weights between neighboring pixels are defined by the pixel similarity. The min-cut algorithm is used to divide the graph. It finds the minimum cut of the weighted graph. Finally, pixels connected to the S node become foreground and pixels connected to the T node become background.

5 Implementation

5.1 Contrast enhancement

The input for the method is an image from magnetic resonance. Background of the image is typically black and tumors have high intensity. However, data are scanned with various settings which causes differences of the intensities. It means that on some images background is not black and tumors are not so intense. For this reason, rescaling is the first step of the proposed method. It is helpful for future processing, because images have similar characteristics. Hence, image is rescaled into the range from 0 to 255. Figure 3 shows input MRI image and the rescaled image.

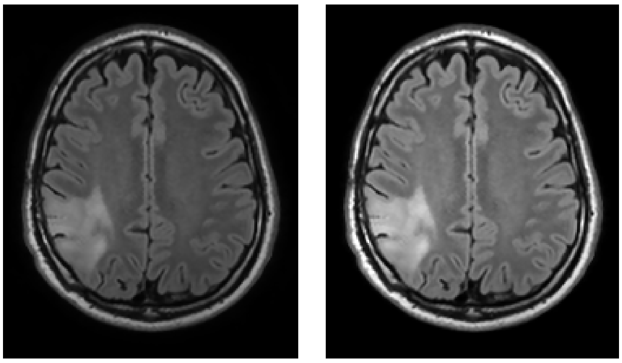

Figure 3: Input MR image (left) and the rescaled image (right).

The scaling results from the minimal and maximal value of the image. Actually the real minimal and maximal values of the image could be just some single casual pixels which are not relevant values for the rescaling. For this reason, a statistical method is used to count the minimal and maximal values used in the rescaling process. Hence, the values of percentile 35 and percentile 99.9 are calculated. This is because the typical large black background of MR images area covers at least 35% of the image and the relevant high intensity area (cranium) covers at least 0.1% of the image.

5.2 Cranium removal

Before the segmentation, the cranium has to be removed from the image. Mainly in cases when cranium pixels have comparable values to the ones of the tumors. High intense cranium cause errors in the segmentation. Some examples are shown in Figure 4.

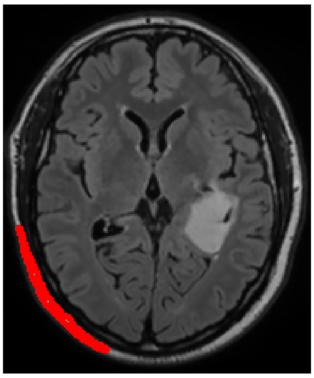

Figure 4: Example of the error segmentation caused by intesive cranium.

Cranium is removed depending on the mask created during the step. Mask creation is derived from the results of statistical method called *Mixture of Gaussians* and adaptive thresholding.

First, *Mixture of Gaussians* is done using distribution of three Gaussians. Three values are the result of the method. One represents black background and two following values represent brain pixels. Historam of the image with Gaussian distribution are shown in Figure 5. Resulting values are used as input parameter for the next step binary thresholding.

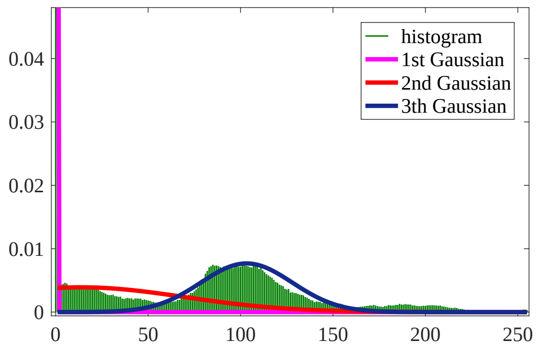

Figure 5: Histogram approximation using *Mixture of Gaussians*.

Parameter called threshold is usually fixed constant, but thanks to the results of *Mixture of Gaussians* method our thresholding is adaptive. The result of thresholding is a mask which marks brain with cranium. It is shown in the Figure 6. This is an important step for the correct removal of the cranium. Morphological operations erode and dilate are used after the thresholding to remove small seeds from the mask. Results of morphological operation are visible in Figure 7.

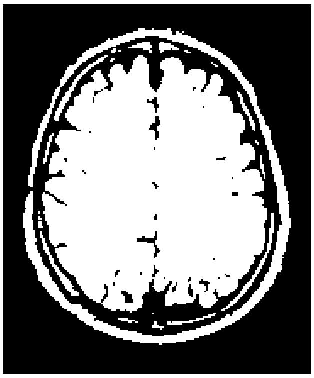

Figure 6: Brain mask created after thresholding.

Next step of the algorithm is graph cut segmentation. The *GrabCut* method from the OpenCV library is used. The method needs input rectangle or a mask which represents foreground. The rest is background. In this step rectangle is used as foreground initialization to prevent removal of the brain mass parts (brain without the cranium). Initial rectangle is created depending on the previous thresholding as shown in Figure 7. *GrabCut* is explained in chapter 4.5. Result is contour which border brain and also cranium.

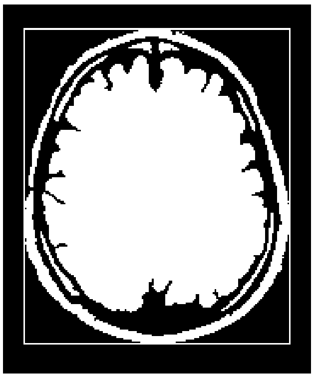

Figure 7: Initial rectangle for *GrabCut*.

Thickness of the contour is enlarged and used as mask for cranium removal. The mask is shown in Figure 8. The result is the image with removed cranium as shown in the Figure 9.

Our testing dataset contains various MR images. Actually some of them have low and other high intense cranium. Whole images are processed in cranium removal step. Sometimes cranium is not entirely removed and intensive remnants cause the problem for the segmentation. On the other side, parts of the brain are removed in some

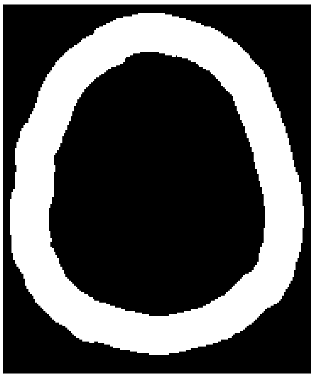

Figure 8: Mask for cranium removal.

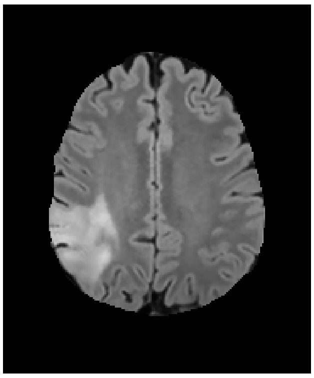

Figure 9: Brain with removed cranium.

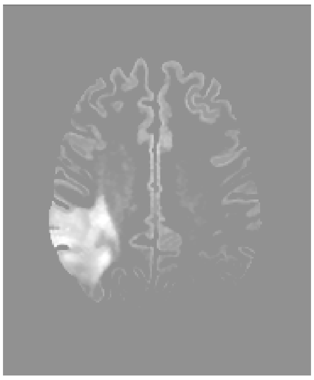

Figure 10: Result of the morphological reconstruction.

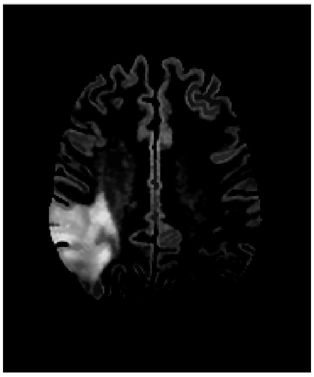

Figure 11: Result of the substraction.

specific cases. However, the second problem does not cause errors in tumor segmentation, so it is not a priority to solve.

5.3 Tumor segmentation

Last step is the tumor segmentation. The same statistical method *Mixture of Gaussians* is done using distribution of three Gaussians again. From three resulting values, one represents black background, the second one represents high intensive brain parts and last one is the rest of the brain. Values are used as parameters for the future processing.

Next step is greyscale morphological reconstruction. It is implemented in OpenCV library. The method needs two parameters. Input image called mask image and a substraction constant. In our algorithm constant depends on the results of *Mixture of Gaussians* method. Constant is subtracted from the input image and marker image is created. It is explained in the chapter 4.3 in detail. The method removes loacal maximas from the image. Result is shown in Figure 10. However, for our algorithm are important these maximal values. Hence, resulting image is subtracted from the input image. The result of the subtraction is shown in Figure 11.

The next step is binary adaptive thresholding. Constant for the method depends on the *Mixture of Gaussians* again. The result is a mask which marks the most intense brain regions as shown in Figure 12. The biggest region is marked as tumor. If there are a lot of small regions then the most intensive is marked as tumor.Then morphological operations erode and dilate remove small seeds from the mask. The result is a mask (Figure 13) which limits tumor.

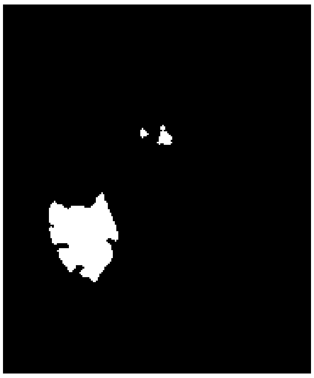

Figure 12: Mask of the most intense regions uf the tumor.

Finally, graph cut algorithm detects boundaries of the tumor. In that case input for the *GrabCut* method is a mask. Mask marks foreground, probably background and background. Foreground is determined by the mask created after adaptive thresholding. It is because changes of the boundaries should not be large. Probably background

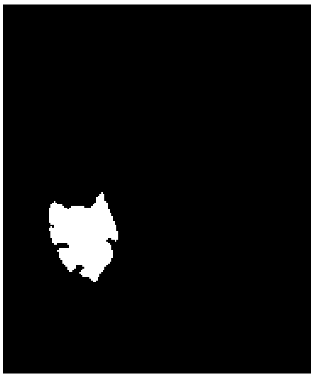

Figure 13: Mask of the tumor.

is a rectangle created from the same mask and the rest is background. Mask for *GrabCut* is shown in the Figure 14.

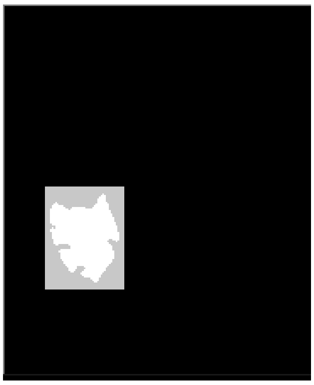

Figure 14: Input mask for the graph cut segmentation.

The last step in our method is the graph cut segmentation optional with the expectation to improve the quality of the segmentation. Visualization of the resulting contours with and without graph cut algorithm is shown in Figure 15. Another segmentations are shown in Figure 16.

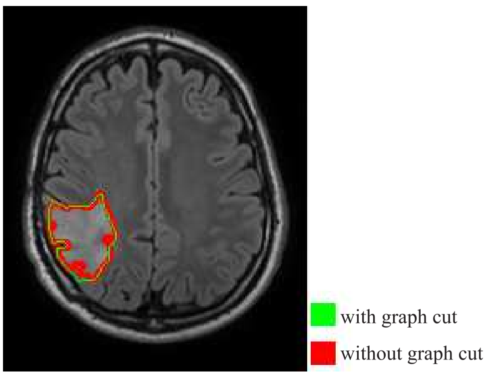

Figure 15: Vizualization of tumor segmentation.

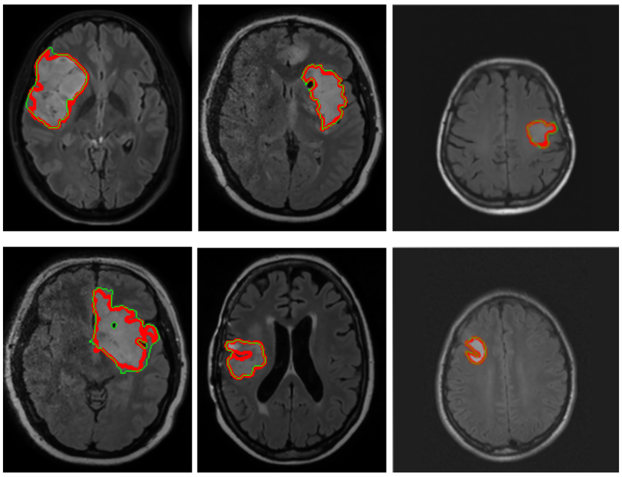

Figure 16: Examples of segmentation.

5.4 Implementation details

MATLAB is used to find the statistical minimum and maximum for contrast enhancement and also for the Mixture of Gaussians method. Output of the previous methods is a file with important statistical values used for the thresholding and morphological reconstruction. These two mentioned methods and the graph cut algorithm are implemented using the C++ programming language and the OpenCv library which includes all important methods of computer vision.

6 Results

Algorithm was tested on real MRI data gained of anonymous patients acquired in clinical practice. Magnetic resonance images came from various apparatus and were scanned with various settings, so they have different intensities.

The images for our dataset were selected from 3D MRI data witch were scanned with T1 relaxation. For the evaluation of our method, we have used 150 randomly selected 2D images with various measurements and intensities, which include tumors of different areas, shapes and locations.

Tumor segmentation was tested by two ways to detect advantages and disadvantages of proposed algorithm. First, it was tested with the algorithm which consists only of adaptive greyscale morphological reconstruction and adaptive thresholding without the graph cut algorithm. Second, it was tested also with the graph cut algorithm.

Algorithm results were compared with manual segmentations of tumors provided by experts. Verification was based on the per pixel comparison of the segmentation results and manual segmentations. Resulting segmentation was transformed to binary image. It is because manual segmentation was also saved as binary image.

Resulting tumor segmentation was divided on true positive (TP), true negative (TN), false positive (FP) and false negative (FN) regions. TP represents pixels where tumor was detected and should be. TN means that tumor was not detected and should not be. FP is when tumor was detected and should not be. Finally if tumor was not detected, but should be, it is FN. Figure 17 is visualization of pixel division. Statistical methods were used to evaluate results:

- true positive rate – sensitivity (TPR):

$$TPR = \frac{TP}{TP + FN}$$

- true negative rate – specificy (TNR):

$$TNR = \frac{TN}{TN + FP}$$

- predictive value positive – precision (PVP):

$$PVP = \frac{TP}{TP + FP}$$

- accuracy (A):

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

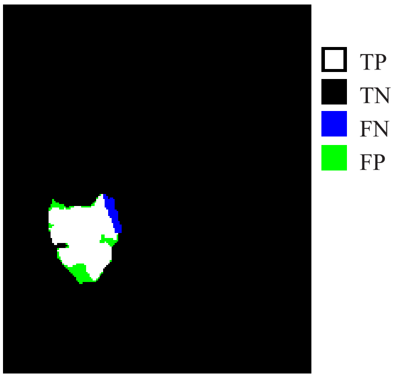

Figure 17: Vizualization of per–pixel division.

Success of the algorithm without graph cut segmentation is presented in the Table 1. In the Table 2 is presented success of algorithm with graph cut segmentation.

TPR	TNR	PVP	A
80.91%	99.75%	83.94%	99.28%

Table 1: Results of testing without graph cut agorithm.

Segmentation without graph cut algorithm reached 99.28% accuracy and true positive rate was 80.91%. Segmentation with graph cut algorithm failed in several cases. It means that no tumor boundaries have been found. It failed in 23 of 150 images what is 14.77%. Correctness

TPR	TNR	PVP	A
82.12%	99.63%	86.4%	99.24%

Graph cut failed in 14.77% of samples. Therefore, only the successful segmentations of the graph cut are presented in the table.

Table 2: Results of testing with graph cut algorithm.

and statistical results was evaluated only on the images where algorithm worked. Accuracy with graph cut algorithm was 99.24% and true positive rate was 82.12%.

Advantages of proposed algorithm lie in the ability to handle various data. It can evaluate MR image with various intensities using adaptive methods which depend on statistical intensity values of the image. Adaptive greyscale morphological reconstruction and adaptive thresholding are crucial for successful segmentation and correct localization of the tumor. Graph cut segmentation was also tested to segment the tumors. It increased the precision and accurancy of tumor detection in specific cases. However, the results using graph cut segmentation method are less successful comparing with the method which was done without the graph cut in summary. Boundaries of the tumor are not always clear. It is problematic for graph cut algorithm and causes that sizes of segmentations were bigger than real tumor.

In some specific cases, tumors were not located because they do not have the largest intensity so other more intensive areas were detected as tumor. The most errors were caused by the images which contained eyes or remnants of the cranium. Examples of the errors caused by the eye are shown in Figure 18. Solve those errors were not our priority so images with eyes were removed from our testing dataset. Necessarity of cranium removal is explained in chapter 5.2. Sometimes cranium is not removed and then it causes problems as is shown in Figure 4. Actually, small and very intensive areas should be filtered, but then small tumors can be lost.

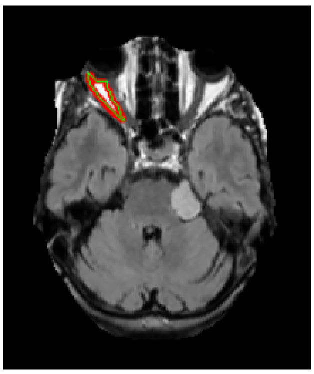

Figure 18: Example of the segmentation errors caused by the eyes.

As was mentioned, algorithm is divided into several smaller steps and implemented in MATLAB and C++. Table 3 shows average time measurements of individual parts of code for one processed image. Time was counted in seconds.

Contrast enhancement		0.005 s
Cranium removal	Mixture of Gaussians	1.761 s
	Segmentation and removal	0.129 s
Tumor segmentation	Mixture of Gaussians	1.189 s
	Segmentation	0.125 s

Table 3: Average time measurements.

7 Conclusions and Future work

In this paper, we have presented automatic algorithm for the segmentation of brain tumors from magnetic resonance images. The main advantage of the presented algorithm is its robustness. It is designed with the goal to process images from various devices for the MRI data acquisition and with various intensities. It becomes possible using the adaptive thresholding and greyscale morphological reconstruction which get parameters according to the results of statistical method *Mixture of Gaussians*. It is followed by the graph cut algorithm. Adaptive thresholding and greyscale morphological reconstruction are crucial for the correct results. The graph cut algorithm increases the precision of the segmentation in some specific cases, but in summary the results using graph cut segmentation method are less successful comparing with the method which was done without the graph cut.

In future work we would like to solve problems with specific cases where sizes and intensities of tumors are problematic. We would like to extend method to segment tumor automatically from 3D MRI data not only 2D images. Then the algorithm will be tested on bigger dataset consists of many 3D MRI data of brains with tumors and compared with another methods.

Acknowledgement: This work was supported by the Grant VEGA 1/0625/14 and Siemens Healthcare Bratislava.

Souce code is available: *http://vgg.fiit.stuba.sk/2016-04/segmentation-of-brain-tumors-from-mri-using-adaptive-thresholding-and-graph-cut-algorithm/*

References

[1] M. A. Balafar, A. R. Ramli, M. I. Saripan, and S. Mashohor. Review of brain MRI image segmentation methods. *Artificial Intelligence Review*, 33(3):261–274, 2010.

[2] N. Gordillo, E. Montseny, and P. Sobrevilla. State of the art survey on MRI brain tumor segmentation. *Magnetic Resonance Imaging*, 31(8):1426–1438, 2013.

[3] M. Havaei, A. Davy, and D. Warde-Farley. Brain Tumor Segmentation with Deep Neural Networks. *arXiv*, page 13, 2015.

[4] H. Khotanlou, O. Colliot, J. Atif, and I. Bloch. 3D brain tumor segmentation in MRI using fuzzy classification , symmetry analysis and spatially constrained deformable models. *Fuzzy Sets and Systems*, 160(10):1457–1473, 2009.

[5] J. Liu, M. Li, J. Wang, F. Wu, T. Liu, and Y. Pan. A Survey of MRI-Based Brain Tumor Segmentation Methods. *Tsinghua Science and Technology*, 19(6):578–595, 2014.

[6] T. Maintz. Digital and Medical Image Processing. page 341, 2005.

[7] B. H. Menze, A. Jakab, S. Bauer, J. Kalpathy-cramer, K. Farahani, J. Kirby, Y. Burren, et al. The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS). *IEEE*, 34(10):1–32, 2014.

[8] S. J. Prajapati and K. R. Jadhav. Brain Tumor Detection By Various Image Segmentation Techniques With Introducation To Non Negative Matrix Factorization. *International Journal of Advanced Research in Computer and Communication Engineering*, 4(3):599–603, 2015.

[9] M. Prastawa, E. Bullitt, S. Ho, and G. Gerig. A brain tumor segmentation framework based on outlier detection. *Medical image analysis*, 8:275–283, 2004.

[10] C. Rother, V. Kolmogorov, and A. Blake. ”GrabCut”: Interactive foreground extraction using iterated graph cuts. *ACM Trans. Graph.*, 23(3):309–314, August 2004.

[11] M. Sezgin and B. Sankur. Survey over image thresholding techniques and quantitative performanc evaluation. *Journal of Electronic Imaging*, 13(1):146–168, 2004.

[12] E. Šikudová, Z. Černeková, W. Benešová, Z. Haladová, and J. Kučerová. *Počítačové videnie*. Wikina, Praha, 1 edition, 2011.

[13] A. S. Torres and F. C. Monteiro. Image segmentation by graph partitioning. *IPB Campus Santa Apolónia*, 805:802–805, 2012.