Image Segmentation using Active Contours without Edges

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ABSTRACT: *Medical images studies that analyse the images help to detect the diseases that are difficult tasks and time consuming. We in this work introduced a model for segmenting the abdominal organs and help to find pathological effect. We have deployed a segmentation method called as Active contours without edges that has not considered the edges for detection. This model enables the quick results and helped to extract the organs. The image segmentation helps to measure the pathology of the affected organs.*

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1. Introduction

The manual segmentation of the medical images is often time-consuming and requires the withdrawal of the attention of the specialist in medical imaging diagnostic. To improve this process is necessary to design and develop computer-aided diagnosis (CAD) tools for medical images. An interesting and challenging task in this area is the segmentation of spleen MRI, segmentation of pathological formations in the spleen and measurements of the organ and the formations for better diagnosis for future medical manipulations or surgery. The human spleen is the largest lymphoid organ in the body and its form and position is variable for each person. Because of the partial volume effect, the gray level of the spleen and grayscale similarity of the adjacent abdominal fat, spleen segmentation has always been a problem [3]. All of these make the segmentation of this organ not very easy task. Segmentation is a key preliminary step in many medical applications such as planning and follow-up procedures, here modeling patients' organs is helpful for both visualization and quantitative measurements [13]. The size of the spleen is giving important information for the health of the human.

The MR diagnostic is often a preferred technique for observation of the abdominal anatomy. MR imaging has been shown to enable accurate volumetric assessment of solid organs in humans [4]. By MRI contrast between the different soft tissues of the body is much greater than those by computed tomography (CT). This makes it especially useful for ontological (cancer) imaging.

There are already a lot of methods for segmentation of abdominal organs, but most of them are for CT not for MR images. In a

previous work (paper [8]) is made a classification of these various methods. According it there are three main classes of methods: gray level based, structure based and texture based. The method we use: "Active Contours without Edges" by Chan and Vese is part of the gray level based methods. Gray level is the most obvious feature of image [5]. These method as all have their advantages and disadvantages, but the algorithm in this paper is combining the best steps to improve the gray level based method and achieve high accuracy and robustness.

2. Gray Level Based Segmentation

2.1 Active Contour Segmentation

The segmentation based on active contour model of Chan and Vese is a gray level based method and is a special case of the Mumford–Shah function. Active contours, or snakes, are computer-generated curves that move within images to find object boundaries. Its 3D version is often known as deformable models or active surfaces in literature [14].

We consider f to be the given grayscale image on a domain &! to be segmented. 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,

$$u(x) = \begin{cases} c_1 \text{ where } x \text{ is inside } C, \\ c_2 \text{ where } x \text{ is inside } C, \end{cases} \tag{1}$$

where C is the boundary of a closed set and c_1, c_2 are the values of u respectively inside and outside of C [1]. By the method of Chan – Vese the purpose is to find among all u of this from the one that best approximates f,

$$arg\ min_{c_1, c_2} c\mu Length\ (C) + vArea\ (inside\ (C)) + \lambda_1 \int_{inside\ (C)} |f(x) - C_1|^2\,dx + \lambda_2 \int_{outside\ (C)} |f(x) - C_2|^2\,dx \tag{2}$$

There are four terms; the first one penalizes the length, the second one – the enclosed area of C to control its size. The third and fourth are penalizing non-compliance between pricewise constant model u and input image f. By finding a local minimizer of this problem, a segmentation is obtained as the best two-phase piecewise constant approximation u of the image f [1]. For the minimizer is needed minimalization over all set boundaries C. This is accomplished by applying the level set technique introduced by Osher and Sethian [1, 9], 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 [6].

2.2 Other Methods

There are a lot of other gray level based methods, but most of them are too old, although they have already shown their potential. Such methods are Region Growing, Deformable models, Graph cuts, Clustering based, Threshold based, Level set, etc. The Region growing method is one of the most popular and studied methods for segmentation. It is also often very effective, but has of course its drawbacks. Most of them are related with the evaluation of the gray level of the target. The problem began when there is a big similarity between the target's gray level and the backgrounds' gray level.

3. Algorithm for Segmentation of Spleen with Pathology in MRI

The Algorithm can be separated in two parts: Segmentation of the spleen and Segmentation of the tumor. The steps in the both parts are similar and are presented in Figure 1. The second block in the diagram in Figure 1 is with interrupted line because it is done only in the first part of the segmentation approach. In the first part we are starting with loading the original MRI of spleen with pathology. Then follows a pre-processing step, consist of contrast enhancement using CLAHE and filtration based on Homomorphic wavelet. The filter is chosen motivating of a previous investigation presented in paper [15].

After this we have to choose the specific parameters for the segmentation based on "Active contour without edges". These are four parameters: mask – Initial rectangular or polygonal ROI 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 region of interest (ROI) is chosen as close to the object as it is possible. Higher values of n are used if the initial contour
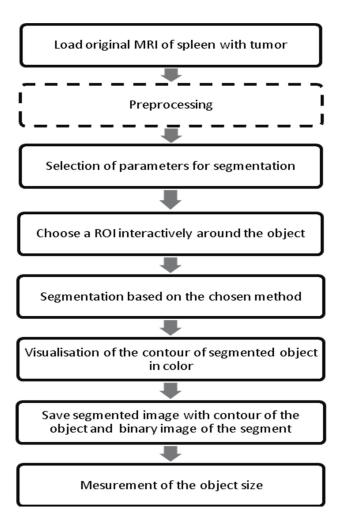
Figure 1. Algorithm for MRI splenic tumor segmentation

position (specified by the region boundaries in mask) is far from the desired object boundaries. R is chosen according to the quality of the processed images and the visibility of the desired organ for segmentation. The preferred values for R are between 1 and 20. The lower values are used by good quality images, where the resolution is big and so is the processing time shorter. Alfa is set between 1 and 10. Higher values of Alpha produce smoother region boundaries but can also smooth out finer details. Lower values produce more irregularities (less smoothing) in the region boundaries, but allow finer details to be captured [1]. With the specified parameters is made the segmentation using the method described in the previous section. As a result we become an image with contoured spleen and a black and white image of the segmented organ.

The second part consists of almost the same steps as by the first one. The difference is that there is no pre-processing step, because we use an image that is already processed and segmented once before

4. Experiments and Analysis

The experiments with the proposed algorithm are made with 20 MRI abdominal images with spleen pathology in different stages. Two of them are chosen to represent the results of the experiments. The image in Figure 2 is showing the original images from an examination of spleen pathology in early and advanced stage. Image (a) is in coronal plane and image (b) is in axial plane and represents the abdominal area in different weights: T2 for image A and T1 for images B-D. The experiments have shown that the results are better by image A in T2, so this image is used for the visualization in this paper. The size of image (a) on Fig.2 is 512x512 pixels and the size of image (b A) is 453x340 pixels. Both of them are in JPEG format. The experiments are made by computer simulation in MATLAB, version 8.1 environment by using of IMAGE PROCESSING TOOLBOXES
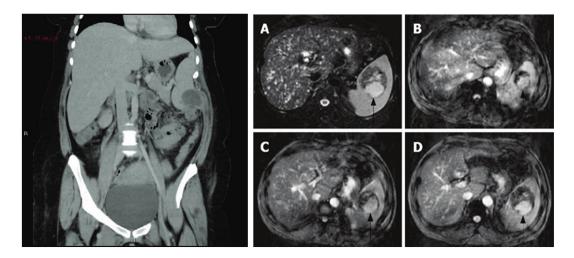
Figure 2. Image (a) is a Case courtesy of Dr David Preston, Radiopaedia.org, rID: 23771. (b) is an original complex MRI. A: In T2-weighted image, a well-circumscribed tumor (arrow) in the spleen; B-D: In T1 contrast-enhancement dynamic study

The obtained images in Figure 3 are segmentation results from the image in Figure 2 (a) with the proposed algorithm in the previous section with the following parameters: $n = 100$, $R = 8$ and Alpha = 1. The image is in coronal plane and the visibility of the spleen is hard, because of the adjacent organs, fat and ribs. However, there are very good segmentation results.
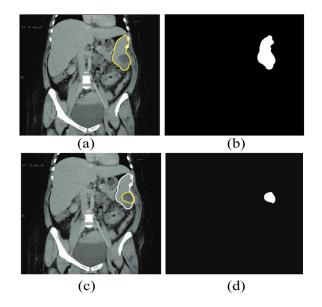

Figure 3. Images (a and c) represent the contour of the segmented spleen and tumor. Images (b and d) are binary images of the segments

The results from the experiment with the image in Figure 2 (b) are shown in Figure 4. The segmentation parameters are set to: n = 30, $R = 10$ and Alpha = 1. The obtained images are showing very good smoothed and solid contour of the spleen and its pathological formation.

Beyond the visualization results, there is also a comparison of our method with another gray level based method – Region Growing. An example with the obtained images after Region Growing segmentation of the image in axial plane is shown in Figure 5. The tests have shown that the Region Growing method is wares by segmenting the splenic tumor, because it consists of parts with very big intensity difference and as a result not the whole tumor is segmented. Also the segmentation of the whole organ is not very good, because some adjacent formations are also contoured and the original form is distorted.
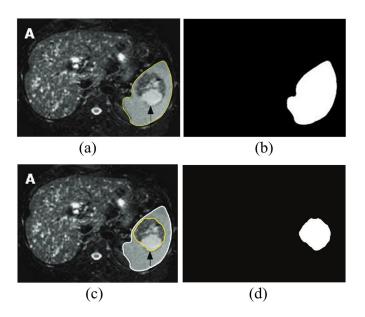
Figure 4. Images (a and c) represent the contour of the segmented spleen and tumor. Images (b and d) are binary images of the segments
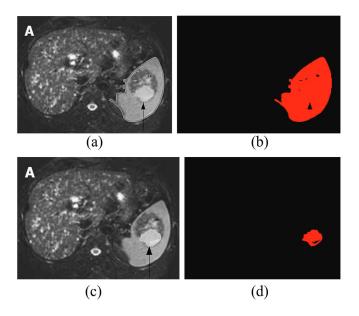

Figure 5. Images (a) represents the contour of the segmented spleen with use of threshold for max. intensity difference 0.27 and (b) represents the contour of the segmented tumor with use of threshold for max. intensity difference 0.05. Images (b and d) are images of the segments

For the comparison is also used the Dice similarity coefficient between the result images of the methods and the ground true (manual segmentation). The Dice Similarity difference is calculated based on the formula below:

$$Dice = \frac{2 \, | \, Smanual \cap Smethod \, |}{| \, Smanual \cap Smethod \, |} \times 100\% \tag{3}$$

where S_{manual} and is the binary segment from the manual segmentation and S_{method} is the binary segment from the used method. The obtained average values for all experiment images are presented in Table 1. The Table shows that the proposed method has

the highest coefficient by both the spleen and the tumor. Also heir is made the conclusion that the pre-processing step as the filtration of the images is very important for the final segmentation results.

Segmentation method with used images	Spleen Dice coefficient (%)	Tumor Dice coefficient (%)
Active contour without edges with filtered images	91.65	90.54
Active contour without edges with unfiltered images	74.29	86.58
Region Growing with filtered images	85.66	60.38

Table 1. Accuracy of segmentation methods for the spleen and the tumor based on dice similarity difference

For evaluation of the splenic malformation some measurements are made and a comparison with a segmented abdominal MRI of a healthy persons. This images are taken from a study of health in Pomerania (East Germany) (Figure 6).

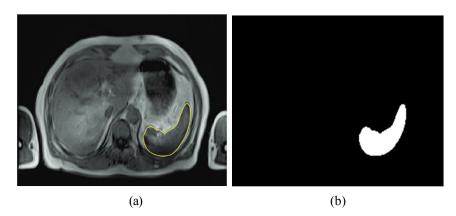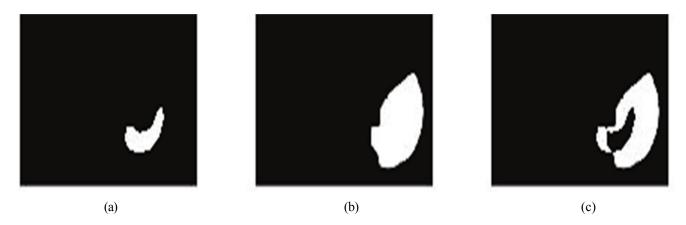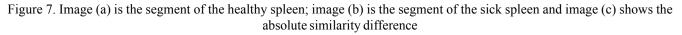(a)   (b)

Figure 6. Images (a) represent the contour of the segmented healthy spleen. Image (b) is a binary image of the segment

For this part of the experiment the images were resized to the size of the images from the study, because they were originally very small (256 × 176 pixels). In Figure 7 is shown the absolute difference between a segmented healthy spleen and a segmented unhealthy spleen. It is obvious that the sick one is much bigger. The size of the normal spleen is calculated with the Euclidian distance and for the visualized images in this paper is 49.35 × 60.83 pixels. Measurements are made in its brightest and its highest part. The size for the abnormal spleen is 71.49 × 106.43 pixels. The size of the splenic tumor is 49.04 × 52.08 pixels.

(a)   (b)   (c)

Figure 7. Image (a) is the segment of the healthy spleen; image (b) is the segment of the sick spleen and image (c) shows the absolute similarity difference

5. Conclusion

In this paper is presented a semi-automated segmentation approach for splenic tumor based on "Active contours without edges" by Chan and Vese method. The experiments show that the robustness and the accuracy of it are very high. The Dice coefficient for the spleen segmentation is 91.65% and for the splenic tumor – 90.54%. As future work we are planning to develop the method to segment a whole sequence of MRI abdominal images with pathological formations, calculate the volume of the spleen and the tumor and make an algorithm for evaluation of the spleen abnormality and human health.

Acknowledgement

References

[1] Getreuer, P. Chan and Vese Segmentation, IPOL 2012-08-08, Yale University.

[2] Behrad, A., Masoumi, H. (2010). Automatic Spleen Segmentation in MRI Images using a Combined Neural Network and Recursive Watershed Transform, IEEE 10th Symposium on neural network applications in Electrical Engineering, *Faculty of Electrical Engineering*, University of Belgrade, Serbia, (September).

[3] Jiang, H., Ma, Z., Zhang, B., Zhang, Y. A Spleen Segmentation Method Based on PCAISO, Software College, Northeastern University, Shenyang, Liaoning, China.

[4] Farraher, S. W., Jara, H., Chang, K. J., Hou, A., Soto, J. A. (2005). Liver and Spleen Volumetry with Quantitative MR Imaging and Dual-Space Clustering Segmentation, *Radiology*, 237 (1) 322-328, (October).

[5] Luo, S., Li, X., Li, J. (2014). Review on the Methods of Automatic Liver Segmentation from Abdominal Images, *Journal of Computer and Communications*, 2 (1-7), Published Online January 2014.

[6] Gergieva, V., Ermakov, S. (2016). GUI for CT Image Segmentation via Active Contours, *In*: 4th International IEEE Black Sea Conference on Communication and Networking, 6-9 June 2016, Varna, Bulgaria.

[7] Chan, T., Vese, L., (2001). Active Contours Without Edges, IEEE Transactions on Image Processing, 10 (2) 266-276.

[8] Mihaylova, A., Georgieva, V. (2016). A Brief Survey of Segmentation Techniques applayd in MRI and CT, *In*: 11th International Conf. on Communications, Electromagnetism and Medical Applications (CEMA'16), Athens, Greece.

[9] Osher, S., Sethian, J. A. (1988). Fronts Propagating with Curvature-Dependent Speed: Algorithms Based on HamiltonJacobi Formulations, *Journal of Computational Physics*, 79 (1) 12-49, http://dx.doi.org/10.1016/0021- 9991(88)90002-2

[10] Hegenscheid, K., Kühn, J. P., Völzke, H., Biffar, R., Hosten, N., Puls, R. (2009). Whole-Body Magnetic Resonance Imaging of Healthy Volunteers: Pilot Study Results from the Population Based SHIP Study, Rapid Communication, 181 (8) 748-759.

[11] Volzke, H. (2011). Cohort Profile: The Study of Health in Pomerania, *International Journal of Epidemiology*, vol 40, p. 294-307.

[12] Wang, Z., Bovik, A. C., Sheikh, H. R., Simoncelli, E. P. (2004). Image Qualifty Assessment: From Error Visibility to Structural Similarity, IEEE Transactions on Image Processing, 13 (4) 600-612, (April).

[13] Gauriau, R., Ardon, R., Lesage, D., Blochy, I. Multiple Template Deformation. Application to Abdominal Organ Segmentation, *International Symposium on Biomedical Imaging ISBI'*15, p. 359-362.

[14] Xu, C., Prince, J. L. Active Contours, Deformable Models, and Gradient Vector Flow.