Contour Detection Results

After extracting the tumor region from the 512*512 original image through the fast RCNN algorithm, it is necessary to do a segmentation of the tumor and produce a tumor mask. As the first step of the segmentation process image preprocessing was done. In there, adjust the image contrast, brightness level and the sharpness of the images. After applying the preprocessing techniques Morphological Active Contours (Morphological chan verse) technique was applied to identify the tumor region.

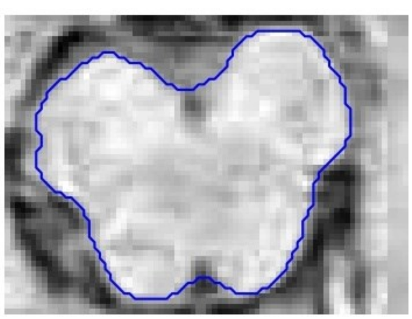
The main idea in active contour models or snakes is to evolve a curve, subject to constraints from a given image in order to detect objects in that image. The typical edge detection algorithms or the snake algorithms use the gradient of the image to identify the edges and stop the evolving curve on the boundary. Because all these typical snakes and active contour algorithms used for edge detection, depending on the image gradient, to stop the curve evolution, these models can detect only objects with edges defined by gradient. If the image is too noisy, then it is needed to preprocess the image before apply the contour algorithm. Usually Gaussian smoothing filter is used and then the edges also going to be smooth. Therefore the typical edge detection algorithms could be failed.

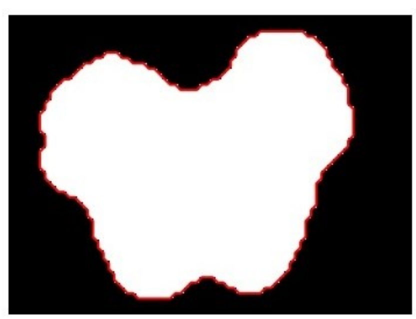
While many segmentation methods rely heavily in some way on edge detection, the "Active Contours without Edges" method by Chan and Vese ignores edges completely. Instead, the method optimally fits a two-phase piecewise constant model to the given image. The segmentation boundary is represented implicitly with a level set function, which allows the segmentation to handle topological changes more easily than explicit snake methods. The Chan-Vese algorithm uses vibrational calculus methods to evolve the level set function. Vibrational methods work by seeking a level set function that minimizes some functional. [1] [2] [3] [4]

Results

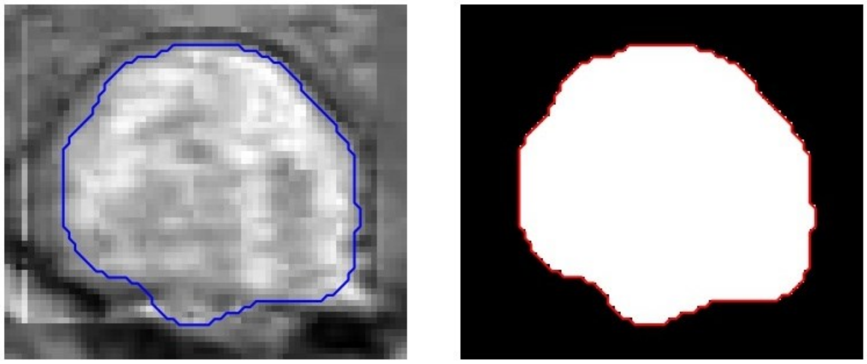
In the following figures show the extracted tumor region from the 512*512 image and the resultant segmentation by applying the contour detection algorithm. Gray scale image and binary image were shown.

Tumor 1

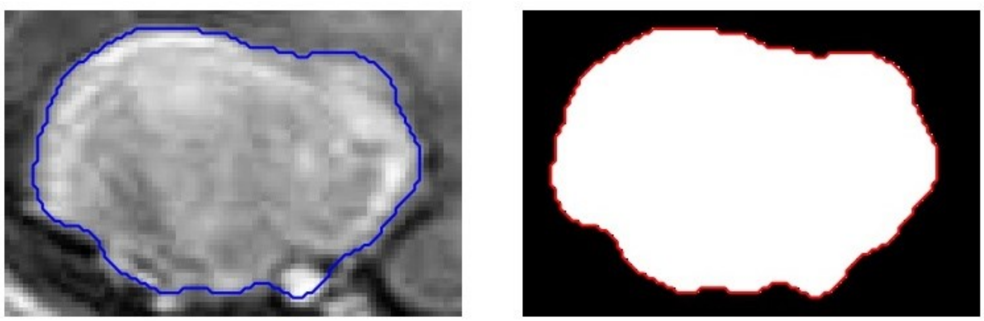




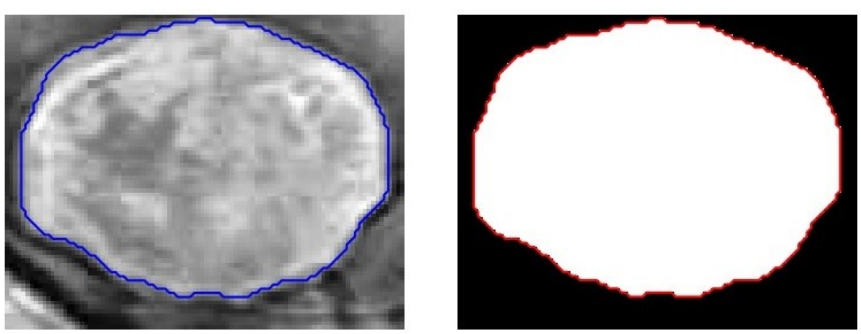
Tumor 2



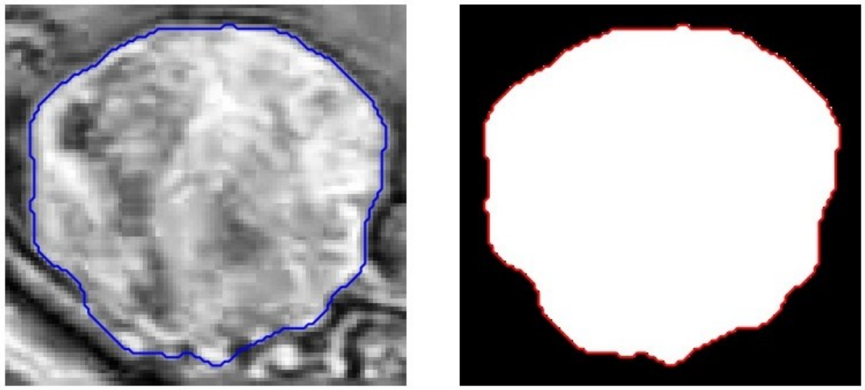
Tumor 3



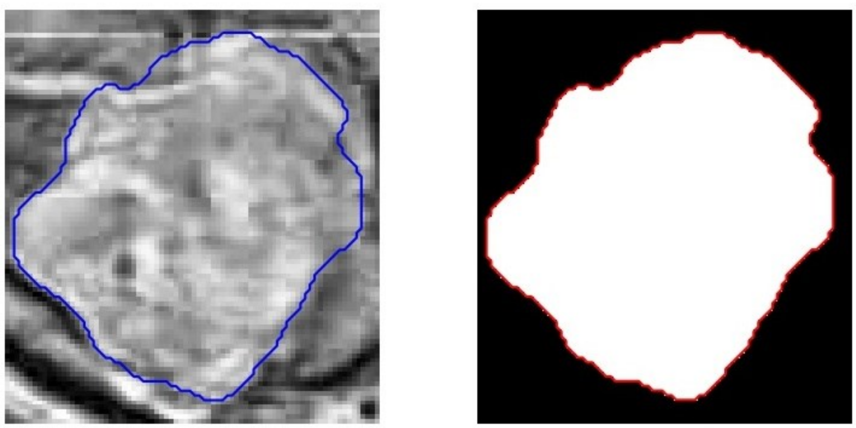
Tumor 4



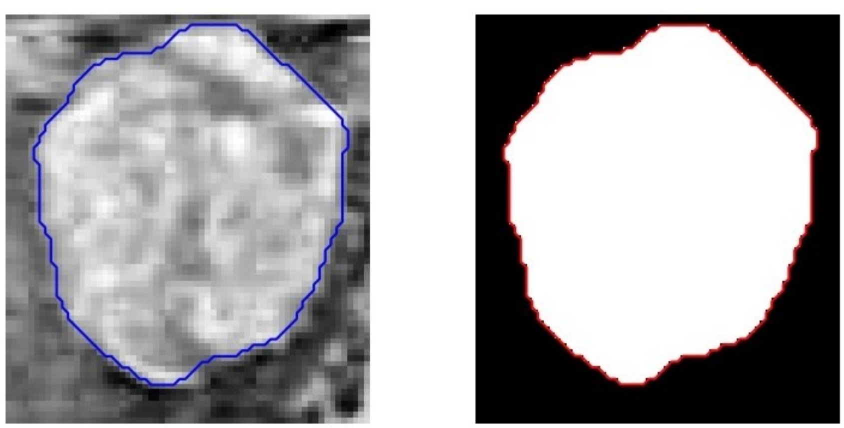
Tumor 5



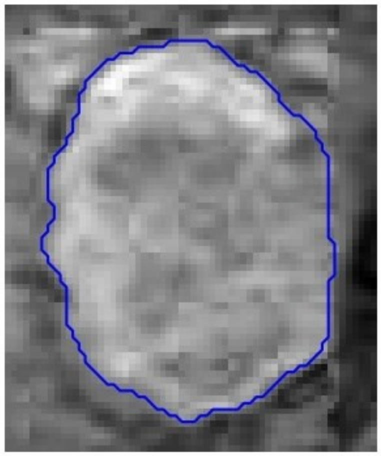
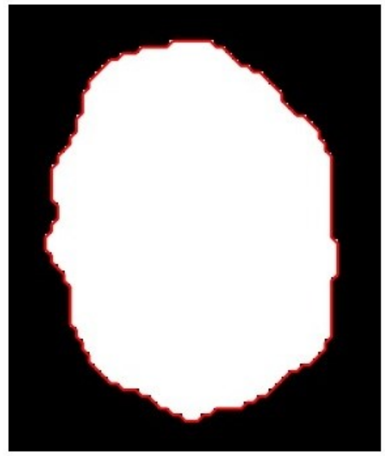
Tumor 6



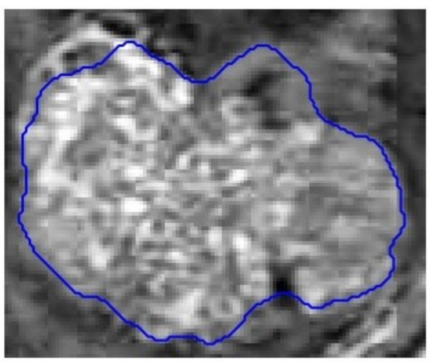
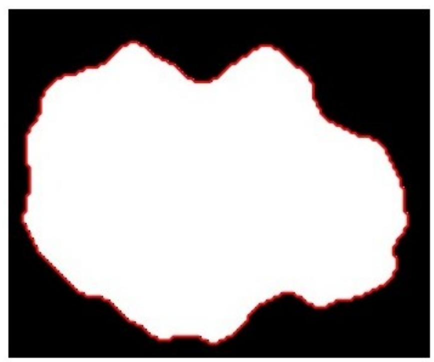
Tumor 7



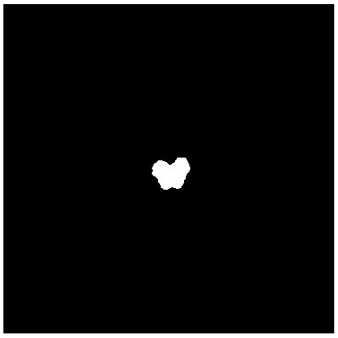
Tumor 8

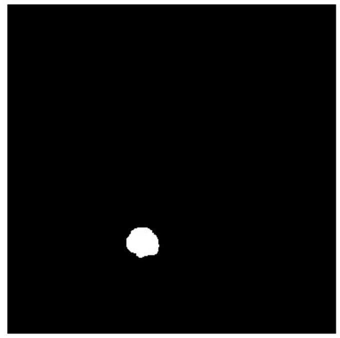
Tumor 9

The obtained tumor masks for all the test images were shown in following figures. These masks are in the 512*512 resolution and image type as a binary.



Tumor 1



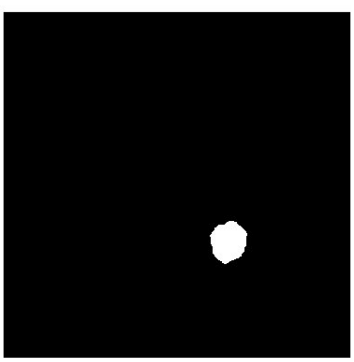
Tumor 2

Tumor 3

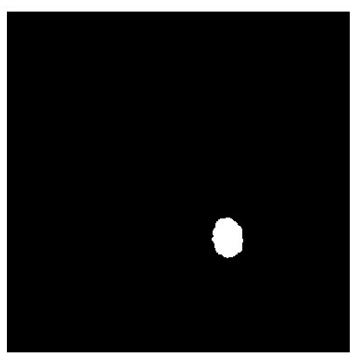
Tumor 4

Tumor 5

Tumor 6



Tumor 7



Tumor 8

Tumor 9

Performance evaluation

For the performance evaluation process, the mask given in the data set was taken as the ground truth and the mask obtained from the prediction process was taken as the test mask. RI, VOI, GCE, BDE, PSNR and MAE were taken as the performance measure parameters. The obtained results were shown in the following figure.

Tumor	1	2	3	4	5	6	7	8	9
RI	0.9806	0.9972	0.9953	0.9967	0.9955	0.9925	0.9961	0.9988	0.9914
VOI	0.0862	0.0212	0.0342	0.0281	0.0376	0.0512	0.0309	0.0116	0.0656
GCE	0.0038	0.0024	0.0040	0.0031	0.0044	0.0061	0.0035	0.0012	0.0083
BDE	38.8477	1.8100	2.1898	1.3171	1.7234	3.5956	2.2962	0.6348	3.0924
PSNR	20.0996	28.5269	26.2755	27.8105	26.4990	24.2554	27.1353	32.1988	23.6240
MAE	635.50	91.28	153.29	107.65	145.60	244.08	125.76	39.19	282.28

Discussion

The value of GCE, VOI and BDE must be low and the rand index should be high for good segmented images. The rand index for all the test images were shown very high value, but the first image has less number compared to the others. VOI, GCE and the BDE should be zero for the accurate prediction. The first and the 9th image has somewhat large VOI values compare to the rest of the images. The BDE value of the first image is very high and its MAE also very high. Therefore this predicted mask can be categorized as a wrong prediction. More well as the 5th and 9th mask also have very poor values than the others so that one can also be categorized as a wrong mask.

Appendix

[5] [6] [7]

A. The Rand Index (RI)
   Rand index counts the fraction of pairs of pixels whose labeling are consistent between the computed segmentation and the ground truth image. Rand measure is a measurement of the similarity between two data clusters. RI lies between 0 and 1, if the two images are identical, the RI should be equals to 1.

B. Variation of Information (VOI)

The variation of information matric defines the distance between to segmentations as average conditional entropy of one segmentation given the other and thus measures the amount of randomness in one segmentation which cannot be explained by the other.

C. Global Consistency Error (GCE)

The global consistency error measures the extent to which one segmentation can be viewed as a refinement of the other. Segmentation which are related are considered to be consistent, since they could represent the same image segmented at different scale. Segmentation is simply a division of the pixels of an image into sets. If one segmentation is a proper subset of the other, then the pixel lies in as area of refinement and the error should be zero.

D. Boundary Displacement Error (BDE)

The boundary displacement error measures the average displacement error of one boundary pixels and the closet boundary pixels in the other segmentation. Particularly, it defines the error of one boundary pixels as the distance between the pixels and the closets pixels in the other boundary.

E. Mean absolute error (MAE)

Mean absolute error is the average of the difference between predicted and the actual values in all test cases; it is the average prediction error. MAE indicates that higher the values of MAE mean the image is of poor prediction. MAE is a quality used to measure how close forecasts or prediction are to the eventual outcomes.

Reference

[1] P. Getreuer, “Chan – Vese Segmentation Simplified Mumford – Shah Model Level Set Functions,” vol. 2, pp. 214–224, 2012.

[2] R. Crandall, “Image Segmentation Using the Chan-Vese Algorithm,” 2009.

[3] T. F. Chan and L. A. Vese, “Active Contours Without Edges,” vol. 10, no. 2, pp. 266–277, 2001.

[4] T. F. Chan, B. Y. Sandberg, and L. A. Vese, “Active Contours without Edges for Vector-Valued Images 1,” vol. 141, pp. 130–141, 2000.

[5] R. Kumar and A. M. Arthanariee, “Performance Evaluation and Comparative Analysis of Proposed Image Segmentation Algorithm,” vol. 7, no. January, pp. 39–47, 2014.

[6] M.- Shift, L. Variation, N. Cuts, and B. S. Database, “Chapter 5 Segmentation Results and Quantitative Evaluation.”

[7] C. Pantofaru, “A Comparison of Image Segmentation Algorithms,” 2005.