Segmentation of Medical Images using Snake Algorithm

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***Abstract*—In this paper, the active contour model or Snake segmentation has been used and extended in order to be applicable for 3D volumes. For this purpose, it is assumed that the changes from one slice to the other is slight so the initial contour can reshape itself to fit the region of interest in each of the consequent slices. The input is a series of Dicom images and the output is a bunch of snakes that the algorithm putting them together to create a 3D volume of the region of interest. For the visualization purpose, Marching Cube algorithm from VTK library has been used.**

***Index Terms*—Segmentation, 3D, Snake, Active Contours, volume, Medical Image Processing, Dicom, CT Scan**

I. Introduction

Diagnostic imaging is a precious tool in the medical field. The current kind of images such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), digital Mammography and other imaging modalities have provided an effective means for mapping anatomy of a subject noninvasively. These technologies have significantly increased the amount of knowledge about normal and abnormal anatomy and are applicable for medical research and they are a necessary component in diagnosis and treatment planning.

As the number of such images is increasing, the use of computers to facilitate processing and analysis is getting importance. The computer science has an important role in preprocessing and denoising image with low quality, low contrast and high amount of noise. Particularly in radiology tasks, computer algorithms have an important role in the delineation of anatomical structures and regions of interest.

These algorithms are called segmentation algorithms and have a vital role in numerous biological-imaging applications including: the quantification of tissue volumes (1), diagnosis (2), localization of pathology (3), study of anatomical structure (4), treatment planning (5), and computer-integrated surgery (6) [1].

Segmentation can be applied to the 2D images and 3D images as well. Some 2D domains segmentation are extendable to 3D.

Segmentation methods can be divided into several groups. In this section, some of the segmentation methods are introduced:

A. Freely deformable models:

Kass et al. introduced the use of deformable models for image segmentation and they called it Snakes [3]. Their main idea is that the evolution of model is driven by two energies: an external energy which its goal is to adapt the model to the image data and an internal energy that stabilizes the shape based on general smoothness constraints. This method is the base of the algorithm suggested in this paper.

B. Level-sets

Osher and Sethian introduced the level-sets methods [4]. But the popularity of them came to computer vision fields by Malladi et al. paper because they combined the idea of the level-sets method with shape modeling [5]. This method is based on the ideas developed by Osher and Seithian to model propagation solid/liquid interfaces with curvature dependent speeds. The interface of front in their method is a closed hypersurface that flows along its gradient field with a constant speed that the speed depends on the curvature. It is moved by solving a "Hamilton-Jacobi" equation for a function in which the interface is a particular level set. A speed function derived from image is used to stop the interface in the vicinity of the object boundaries. At the end, the resulting equation of motion is solved using an entropy-satisfying upwind finite difference scheme.

C. Statistical shape models

1) Active Shape Models

This method was presented by Cootes, Taylor and et al. in which they describe 'active shape models' which iteratively adapt to refine the estimate of the pose, scale, and shape of models of image objects [6]. This method uses flexible models derived from training examples. These models are known as Point Distributed Models that represent objects as sets of labeled points. An initial estimate of the location of the model points in the image is obtained by attempting to move each point to a better position nearby. Then the pose variables and shape parameters have to be adjusted and the amount of their adjustment has to be calculated. Their algorithm also considers limits on the shape parameters in order to make sure that the example can only deform into shapes conforming to global constraints imposed by the training set. The algorithm uses an iterative procedure to deform the model example to find the best fit to the image object.

2) Active Appearance Model

Cootes and et al introduced the Active Appearance Models method [7]. They described it as a new method of matching statistical models of appearance to images. A set of model parameters control modes of shape and gray-level variation learned from a training set. The algorithm constructs an efficient iterative matching algorithm by learning the relationship between perturbations in the model parameters and the induced image errors [2].

II. SNAKE METHOD

A snake is an energy minimizing spline influenced by image forces. These forces pull the snake toward some important features of the image such as lines and edges. The other name of Snakes is Active Contour Model. This method can be used for several computer vision problems such as detection of edges, lines, motion tracking and stereo matching. Snakes can be seen as an example of a more general technique of matching a deformable model to an image using energy minimization.

Based on Kass and et. al, a Snake consists of two energy [3]. One internal energy and one external energy. Equation (1) represents the formula for calculating image energy. In this equation E_{int} is representative for the internal energy and E_{image} is the image forces and E_{con} is demonstrative for the external constraint forces. The position of a snake is demonstrated by $v(s) = (x(s), y(s))$.

$$E^*_{snake} = \int_0^1 E_{snake}(v(s))ds = \int_0^1 E_{int}(v(s)) + E_{image}(v(s)) + E_{con}(v(s))ds \quad (1)$$

A. Internal Energy

The internal spline energy can be written as equation (2).

$$E_{int} = (\propto(s)|v_s(s)|^2 + \beta(s)|v_{ss}(s)|^2)/2 \quad (2)$$

In equation (2), to control the behavior of the snake, two parameters $\propto$ and β have to be adjusted properly. The parameter $\propto$ controls the first-order term's behavior and makes it to act like a membrane and the parameter β controls the second-order term and makes it to act like a thin plate.

In order to minimize the internal energy, Euler equation has been used. The details about minimizing the energies are described completely in [3].

III. EXTERNAL ENERGY

A. Image Forces

The image forces consist of three different functions that attract the snake to the salient features of the image including lines, edges, and terminations. The total Image's energy is a weighted sum of these energy functions.

Equation (3) presents the formula of Image Forces as the weighted sum of the energy that attracts the snake to the lines, the energy that attracts the snake to the edges and the energy that attracts the snake to the terminations.

$$E_{image} = w_{line}E_{line} + w_{edge}E_{edge} + w_{term}E_{term} \quad (3)$$

To fit the snake to a different object, these weights need to be readjusted properly.

1) Line Functional

The simplest image function as proposed by Kass and et al. is the image intensity itself. Equation (4) represents the line function. The behavior of the snake is dependent on the sign of w_{line}. If it is positive the snake will be attracted to the light lines otherwise it will be attracted to the dark lines. Instead of image intensity, the intensity of the smoothed image can be used as an alternative. In this paper, a smoothed version of the image is used as line functional. The smoothed images is calculated by applying **itk.SmoothingRecursiveGaussianImageFilter.**

$$E_{line} = I(x, y) \quad (4)$$

2) Edge Functional

This function is used to find the edges of the object. Using the equation (5) as the edge function, the snake will attract to the contours with large image gradients.

$$E_{edge} = -|\nabla I(x, y)|^2 \quad (5)$$

The problem with equation (5) is that it can be attracted to the boundaries from a fairly large distance. So if the image contains other objects with low-energy features, the snakes will try to attract to that feature. In another word, it will trap in local minima. To solve this problem, another different edge-energy function was proposed in [3]. The proposed energy function is brought in equation (6) where G_σ is a Gaussian with a standard deviation of σ. The minima of this function happens on zero-crossing of $G_\sigma * \nabla^2 I^2$ which defines edges based on Marr-Hildreth theory.

$$E_{edge} = -(G_\sigma * \nabla^2 I^2) \quad (6)$$

3) Termination Functional

This function is used to find terminations of line segments and corners. The curvature of level lines can be found in a slightly smoothed image. Equation (7) defines the slightly smoothed version of the image, in which, a Gaussian filter with a standard deviation of σ is applied on the image.

$$C(x, y) = G_\sigma(x, y) * I(x, y) \quad (7)$$

Equation (8) defines the gradient angle that is calculated using the tangent inverse of the first derivative of the smoothed image with respect to y divided by the first derivative of the image with respect to x.

$$\theta = \tan^{-1} C_y/C_x \quad (8)$$

Equation (9) defines the unit vector along the gradient direction and equation (10) defines the unit vector perpendicular to the gradient vector.

$$n = (\cos\theta, \sin\theta) \quad (9)$$

$$n_{\perp} = (-\sin\theta, \cos\theta) \quad (10)$$

Having this information, the curvature of the level contours in $C(x, y)$ is calculated using equation (11)

$$E_{term} = \frac{\partial\theta}{\partial n_{\perp}} = \frac{\partial^2 C/\partial^2 n^2}{\partial C/\partial n} = \frac{C_{yy}C_x^2 - 2C_{xy}C_xC_y + C_{xx}C_y^2}{(C_x^2 + C_y^2)^{3/2}} \quad (11)$$

By combining E_{edge} and E_{term}, a snake that can attract to the edges and termination is calculated.

IV. MINIMIZATION OF ENERGY FUNCTION

Considering $E_{ext} = E_{image} + E_{con}$. We can minimize the formula in equation (1) using two independent Euler Equations.

$$\propto x_{ss} + \beta x_{ssss} + \frac{\partial E_{ext}}{\partial x} = 0 \quad (12)$$

$$\propto y_{ss} + \beta y_{ssss} + \frac{\partial E_{ext}}{\partial y} = 0 \quad (13)$$

Details for solving this minimization problem is brought in [3]. After the minimization process, x and y are calculated using the following equations.

$$x_t = (A + \gamma I)^{-1}(x_{t-1} - f_x(x_{t-1}, y_{t-1})) \quad (14)$$

$$y_t = (A + \gamma I)^{-1}(y_{t-1} - f_y(x_{t-1}, y_{t-1})) \quad (15)$$

V. PROJECT DETAILS

In this project, a method for segmenting 3D medical images is proposed. The main idea is to extend the 2D Snake algorithm to 3D images. For this purpose, a series of Dicom format images were used as input data. As the Dicom series are several slices of the images that happen consecutively. It is expected that the changes from one slice to the other happens slightly. In another word, by drawing a contour around the object of interest in one of the slices, it is probable that the snake changes its shapes in each of the consequent slices to fit to the regions of interest and as a result, it is expected to have the segmented volume using one or few initial contours. The proposed method works well for body organs with slight changes such as femur, kidney and etc.

For covering complex structures, the users are supposed to draw several initial contours. For example, having Hip data set, if the goal is to segment both the femurs at the same time the user needs to draw two initial contours separately for the two femoral.

The contours are B-splines curves made by input control points so the behavior of the snake will be Smooth.

B-spline curves are kind of curves that are very similar to Beizier curve's. The only difference is that it uses B-spline basis functions. The following equation demonstrates a B-spline curve.

$$Q(u) = \sum_{i=0}^{m} P_i N_{i,k}(u) \quad (16)$$

Where $P_0, P_1, \dots, P_m$ are the control points and $u_0, u_1, \dots, u_{m+k}$ are the knot values and $N_{i,k}$ are B-spline curves. The control points here are the points created by drawing the contour. And the order of the spline is $k = 4$ or cubic bspline.

A. *Disadvantages of the proposed method*

- Not applicable for complex structures.
- Not applicable for structures with more than one component unless more than one sketch(drawing contour) is used
- Adjusting the weight is very difficult and time-consuming
- The weights can be different for different images and need a new adjustment
- Applicable on structures with little change in each slice

B. *Advantages of the proposed method.*

- Very low amount of user manipulation.
- Semi-automatic.
- Need for only one or few sketches.
- Acceptable results on simple structures.
- Converting 2D solution to 3D solution

VI. EXPERIMENTAL RESULT

In this part, some of the results obtained by the proposed work are presented. For each of the presented results, the initial contour drawn by the user is provided as well. The ability to draw contour on the image is provided by the Tkinter library of python. The input of the algorithm is the initial contour and weights for adjusting Snake energy function. The algorithm continues with deformation of initial contour so that it can fit the region of interest in the subsequent slices, in another word, the output of the previous slice is the input of the consequent slice. Figure 1 presents the initial contour drawn by the user on the input image and the second row is the 3D volume which is the output of the 3D-Snake algorithm. The dataset used here is Hip dataset and the segmented volume is part of femur bone existed in the dataset.

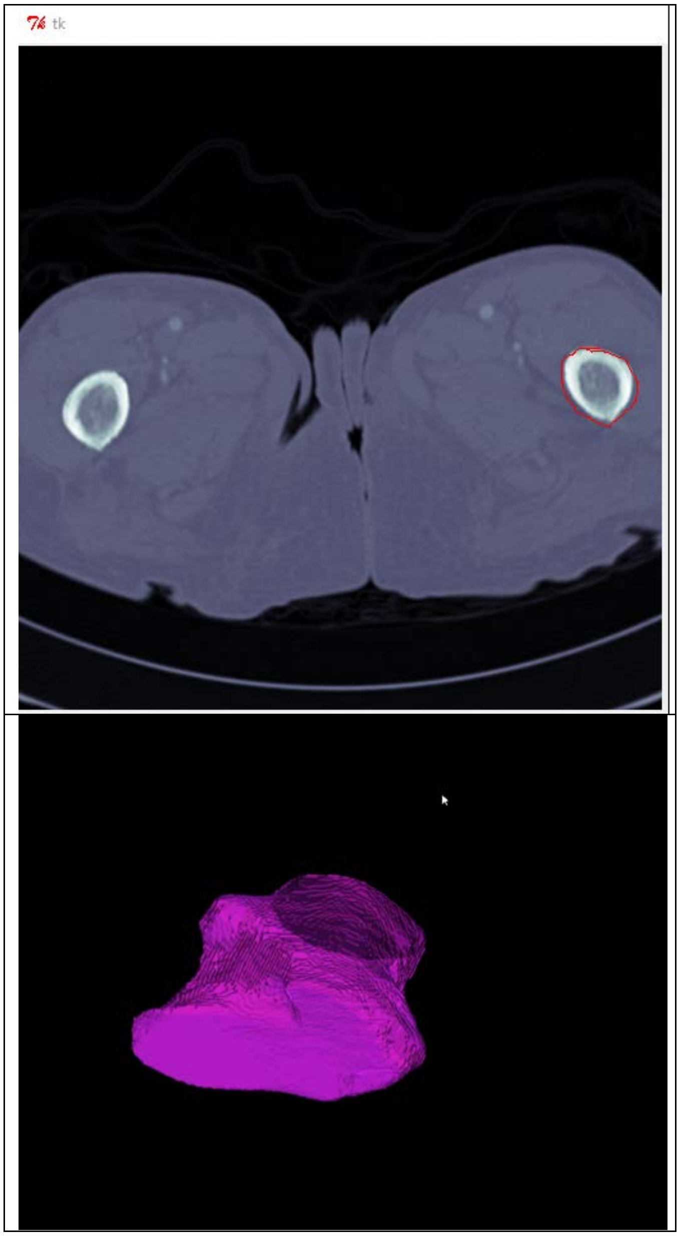

Figure 1- the first row is the image of the initial contour and the second row is the output of the 3D-Snake algorithm for part of the femur bone.

Figure 2 is another result of the 3D snake algorithm in which Hip data set is used again but at this time the algorithm gives the ability to select multiple contours to segment several parts of the volume at the same time. The picture in the top row is the first contour drawn by the user and the second row is the second contour drawn by the user. The picture in the third row is the segmented volume containing two femur bones and created using the proposed 3D Snake algorithm.

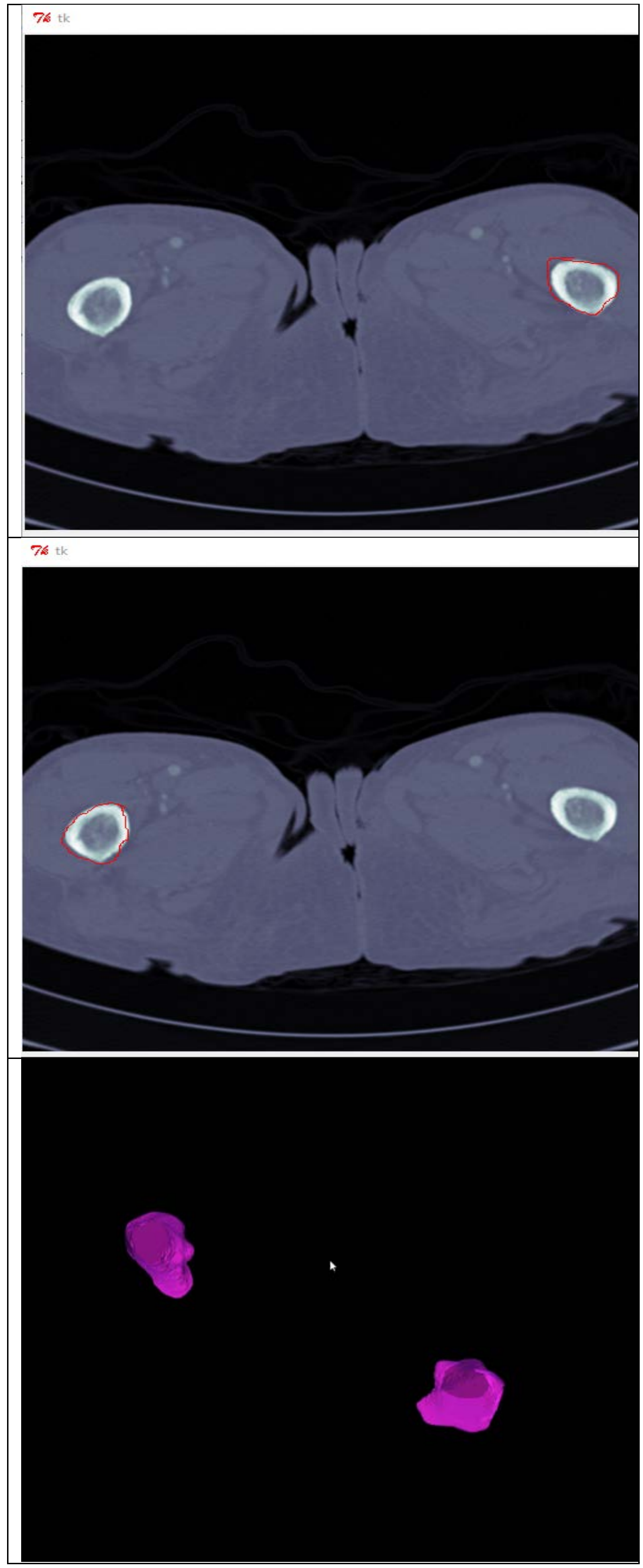

Figure 2- the first row and second row are the images of the initial contours and the third row is the output of the 3D-Snake algorithm for two femur bones related to two legs.

Figure 3 is an example of segmenting lung from the Beaufix dataset obtained from Osirix repository [8]. The image in the first row is the initial contour drawn by the user and the image in the second row is the extracted volume using 3D Snake algorithm.

Figure 3- the first row is the image of the initial contour and the second row is the output of the 3D-Snake algorithm for part of the tubular structure between the two kidneys.

Figure 4 is an example of segmenting Kidney from Beaufix dataset obtained from Osirix repository [8]. The image in the top row is showing the initial contour and the image in the second row is the segmented volume using the proposed algorithm.

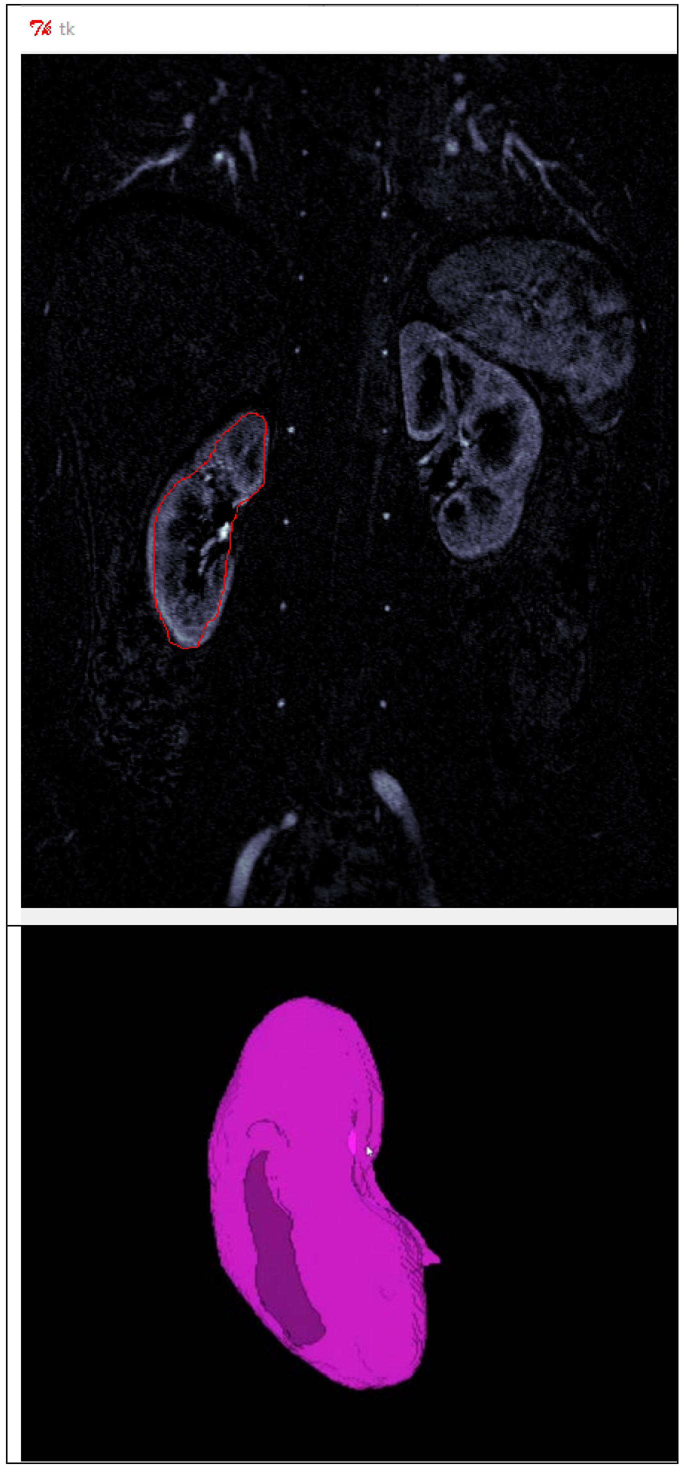

Figure 4- the first row is the image of the initial contour and the second row is the output of the 3D-Snake algorithm for part of the left kidney.

Figure 5 is a complete femur bone picked from the Keskonrix dataset collected from Osirix repository. The top row is the initial contour drawn by the user and the second row is the segmented femur.

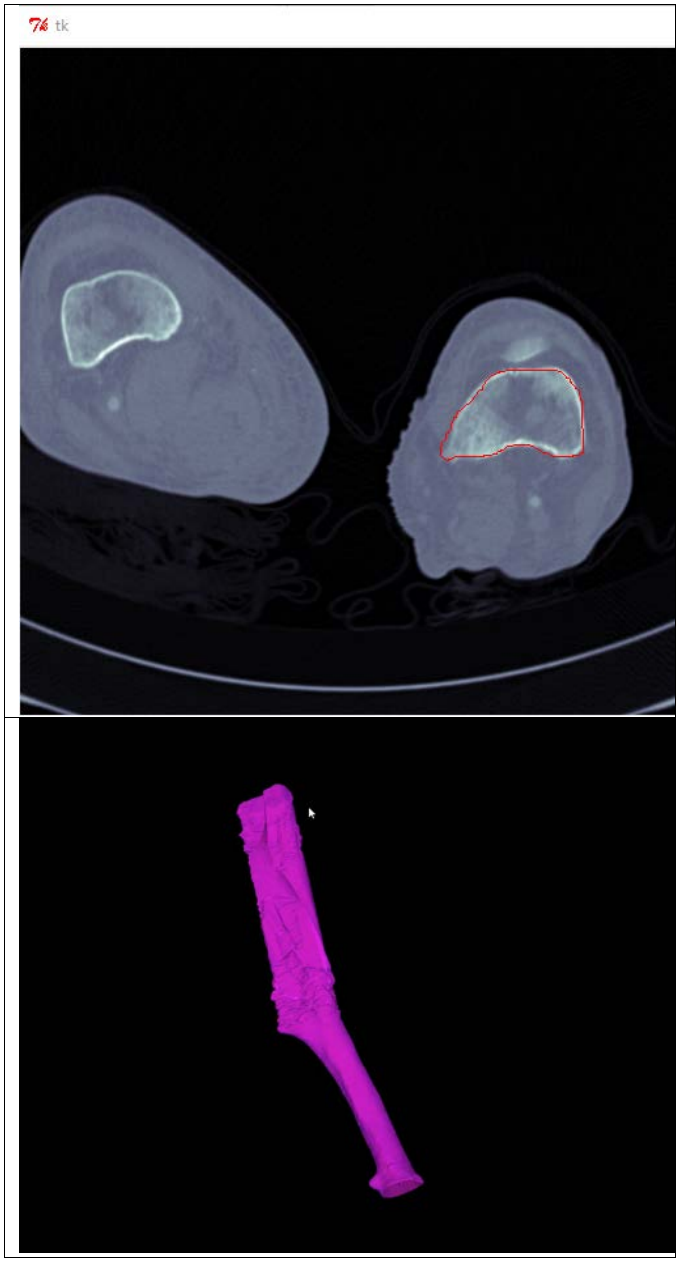

Figure 5- the first row is the image of the initial contour and the second row is the output of the 3D-Snake algorithm for the femur bone.

Figure 6 is using the same dataset as the one used in Figure 5, the only difference is the number of initial contours. Here to segment the two femur bone at the same time and showing them in the same output, two contours are drawn by the user, one for the right femur and the other for the left femur and their corresponding initial contour is shown in the first and second row of the image. In the third row, the segmented femora are demonstrated.

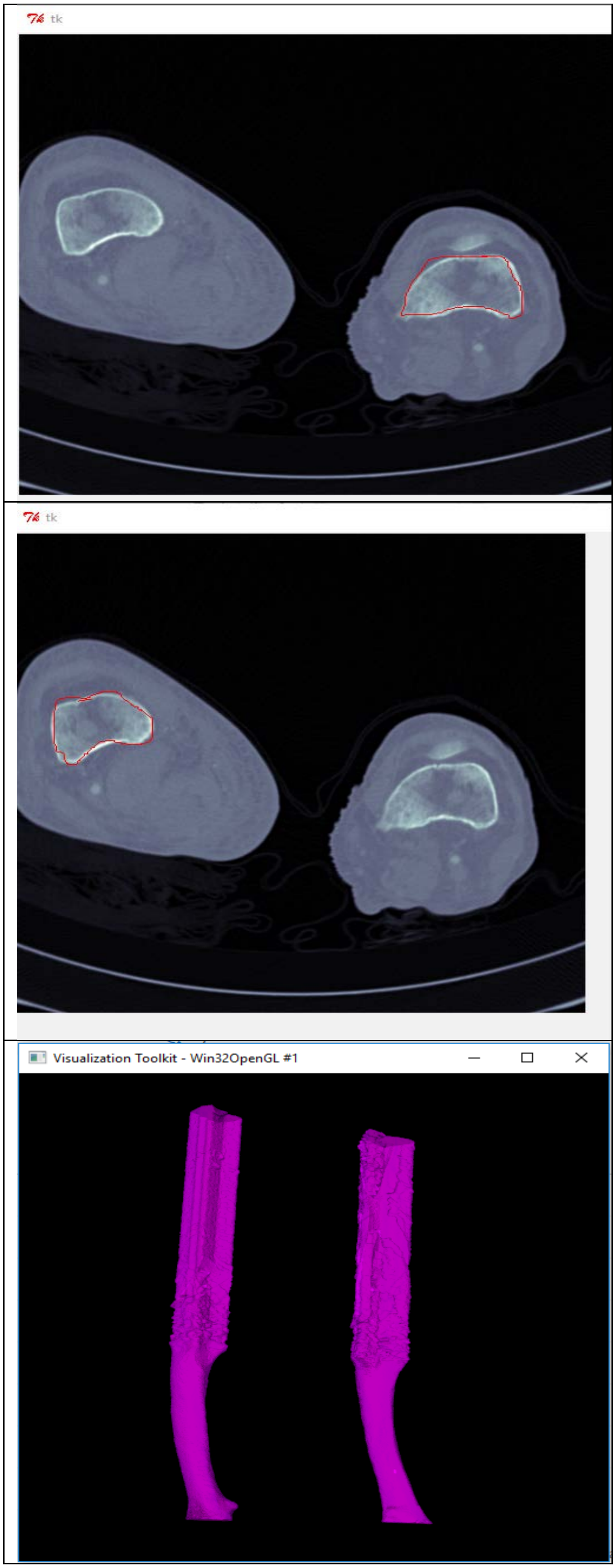

Figure 6- the first row and second row are the images of the initial contours and the third row is the output of the 3D-Snake algorithm for part of the femur bone.

Figure 7 is selected from a dataset related to the University of Calgary and it contains Dicom images related to temporal bone. The first row shows the initial contour drawn by the user and the second row presents the segmented volume.

In all the results for the purpose of visualization the Marching Cube algorithm existed in (visualization toolkit) VTK have been used [9].

Figure 8 is the GUI created for the program using Tkinter library of Python [10]. The GUI is for the convenience of the user. It can help the user to know which parameters he/she has to consider and gives as input to the algorithm. Table 1 contains important information about adjusting parameters and weights of the algorithm; furthermore, a read-me file is attached to the submitted codes. The file contains information about how to run the program and visualize the results.

In order to make it more sensible for the readers, different Snakes at different slices has been shown in Figure 9. This Figure shows the deformation of the Snake in different slices. The slices are from the Hip dataset and the top left image is the initial contour drawn by the user.

Table 1 presents the parameters used for adjusting algorithm for the specified image. The first column is the image ID, the second column is Wedge which is the parameter to control the Snake behavior towards image edges, the third column is Wline which is the parameter to control the behavior of the Snake towards the lines in the image, the fourth column is Wterm which is a parameter to control the behavior of the Snake towards terminations, the fifth column is alpha which is a parameter to control the shrinkage of the Snake, increasing this parameter results in shrinking of the Snake. , the sixth column is beta that is an indicator of smoothness by increasing it the Snake will be smoother, the seventh column is sigma which is the input of the Gaussian smoothing filter, the eighth column is gamma which is the time parameter or the step size, the ninth column is the number of iteration, the tenth column is the name of dataset, the eleventh column is the start slice that is the slice in which the initial contour is drawn, the twelfth column is the end slice that is the slice that the object of interest vanish on that slice and the thirteenth column is the reference to the dataset.

VII. EVALUATION

For the purpose of evaluation. The same part of the femur as shown in Figure 1 was segmented manually. For manually segmenting the volume, the ITK_Snap software was used [11]. The manually segmented volume was used as a ground truth. A screen-shot of the ITK-Snap software and the segmented part is provided in Figure 10. To compare the results of the proposed algorithm with the ground truth, the Dice coefficient was used. Equation (17) presents the formula for calculating Dice coefficient. The Dice coefficient “D” measures the spatial overlap between two binary segmentations such as “A” and “B”.

$$D = \frac{2|A \cap B|}{|A| + |B|} \tag{17}$$

Table 1 shows the result of calculating Dice coefficient for the volume segmented with the proposed algorithm and the manually segmented volume using ITK-Snap. The Dice coefficient for this example is 0.94 that shows the similarity between the two segmented volume.

Table 1 result of the evaluation, calculating Dice coefficient to compare the output of the proposed algorithm and the ground truth

Number of voxels with value 1 using proposed algorithm	270684
Number of voxels with value 1 using the manual method	283877
Dice coefficient	0.9419

VIII. FUTURE WORKS

The current work extends the 2D Snake method on 3D but the root of the work is still working on 2D instead of 3D. The researchers can seek for an original 3D algorithm. It may consider an initial mesh instead of initial contour. However, determining the size of the mesh and its location is not going to be a simple task.

The researchers can also design a segmentation method that needs less effort to adjust the parameters.
The algorithm can ask the user to define a center line for the object of interest and move the contours so that their center is located on the corresponding point of the center line. The center line makes it easier to follow the curvature of the object of interest.

IX. CONCLUSION

Segmentation of 3D images is a crucial step for medical tasks. Using them, the doctors can diagnose different kinds of tumor, cancer, blockage, and etc. There is a bunch of segmentation methods, among which, this paper implements Active contour models or Snake method.

The idea is to extend the 2D snake model on 3D. For this purpose the algorithm gets an initial contour on one of the slices as the input and deforms this initial contour to fit the object of interest. Then for the subsequent slice, the initial contour will be the final snake from the previous contour. Actually, the structure is hierarchical and the output of each slice is transferred to the next slice as the next slice’s input. The suggested algorithm is not applicable to the shapes with a high amount of changes from one slice to the others; however, it works well on structures with a low amount of change such as femur bone, kidney, etc.

The algorithm is very sensitive to the weights, so adjusting the weights to get the best result can be very challenging.

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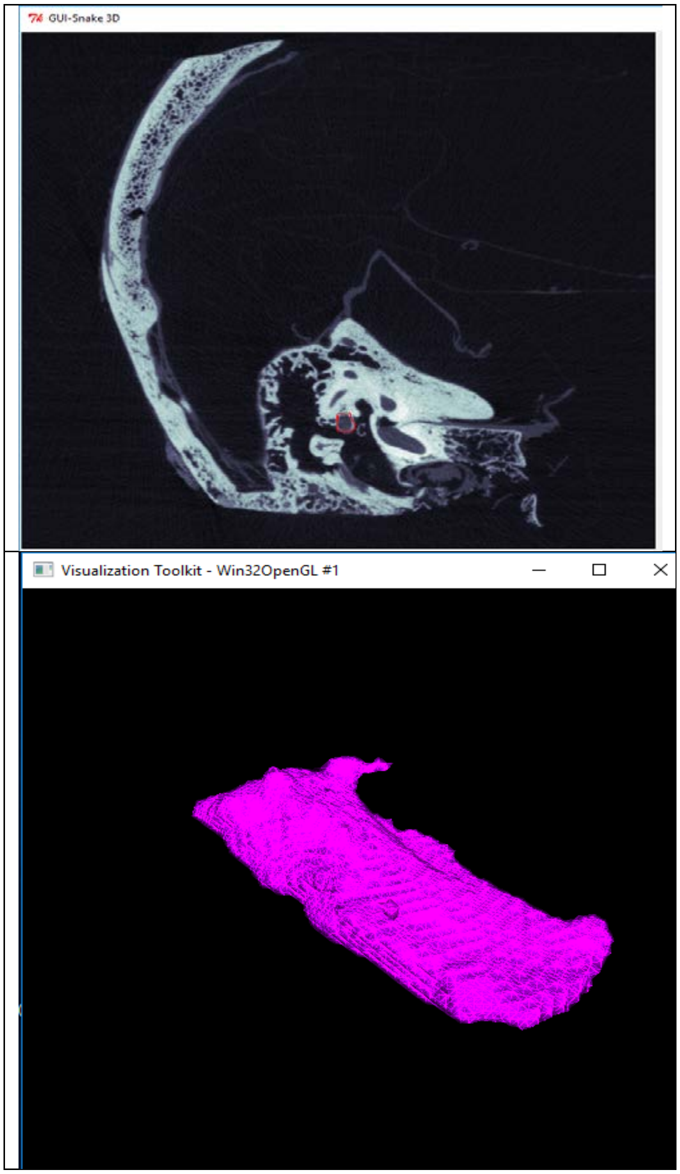

Figure 7- the first row is the images of the initial contours and the second row is the output of the 3D-Snake algorithm for part of the facial nerve in the temporal bone.

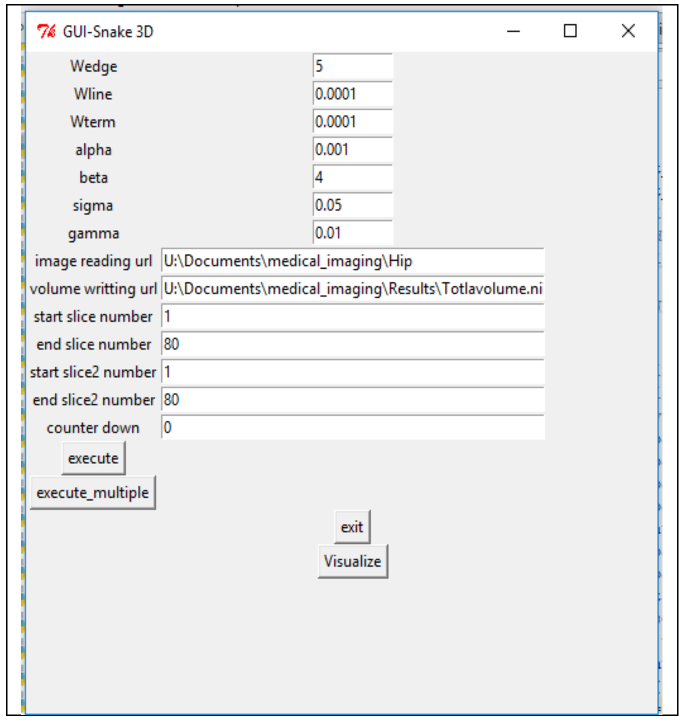

Figure 8- the first row is the images of the initial contours and the second row is the output of the 3D-Snake algorithm for part of the facial nerve in the temporal bone.

Table 2 the parameters used for creating the results and the related datasets

ID	Wedge	Wline	Wterm	alpha	beta	sigma	gamma	n-iteration	dataset	Start slice	End slice	reference
1	5	0.0001	0.0001	0.001	4	0.5	0.01	100	Hip	1	80	Hip dataset
2	5	0.0001	0.0001	0.001	4	0.5	0.01	100	Hip	1	80	Hip dataset
3	5	0.0001	0.0001	0.001	4	0.5	0.01	100	\OsiriX\Beaufix\study\dyn_echo_bh_perfusion _SUB_MIP_COR	10	end	[8]
4	5	0.0001	0.0001	10	40	0.5	0.01	100	\OsiriX\Beaufix\study\SUB_arterial	38	70	[8]
5	5	0.0001	0.0001	0.001	4	0.05	0.01	100	\OsiriX\Keskonrix\study\AngioRunOff_20_B3 0f	498	829	[8]
6	5	0.0001	0.0001	0.001	4	0.05	0.01	100	\OsiriX\Keskonrix\study\AngioRunOff_20_B3 0f	498	829	[8]
7	5	0.0001	0.0001	1	4	0.05	0.01	100	Calgary\TBone-2015\MicroCT\L2501L_EDITED	236	270	University of Calgary

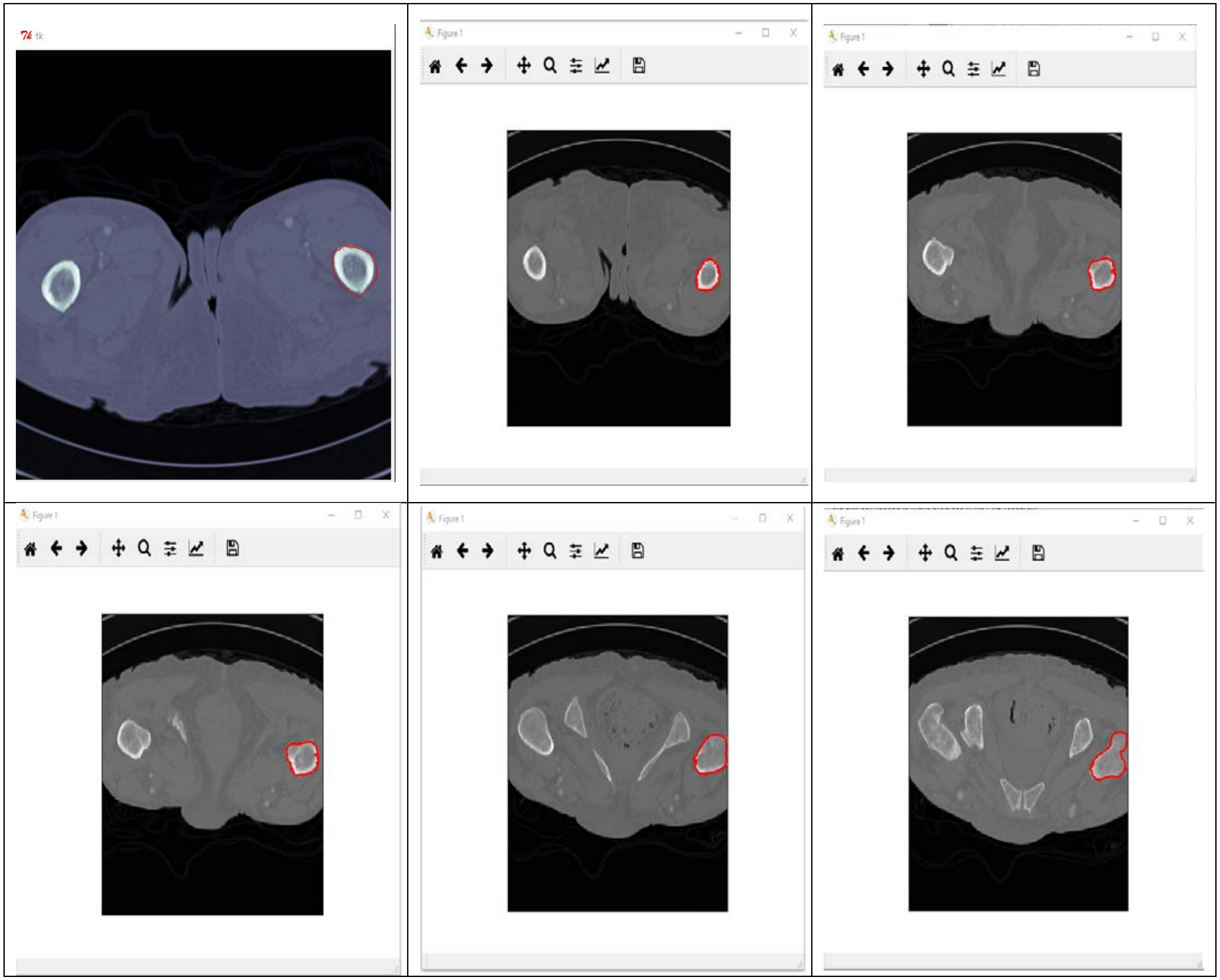

Figure 9-the images presented here are the status of the contours in different time and how they change their shape in order to fit to the region of interest.

Figure 10- ITK-Snap software were used to manually segment the object of interest.