# Semi-automatic active contour approach to segmentation of computed tomography volumes

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## ABSTRACT

In this paper a method for three-dimensional (3-D) semi-automatic segmentation of volumes of medical images is described. The method is semi-automatic in the sense that, in the initial phase, the user assistance is required for manual segmentation of a certain number of slices (cross-sections) of the volume. In the second phase, the algorithm for automatic segmentation is started. The segmentation algorithm is based on the active contour approach. A semi 3-D active contour algorithm is used in the sense that additional inter-slice forces are introduced in order to constrain the obtained solution. The energy function which is minimized is modified to exploit information provided by the manual segmentation of some of the slices performed by the user. The experiments have been performed using computed tomography (CT) scans of the abdominal region of the human body. In particular, CT images of abdominal aortic aneurysms have been segmented to determine the location of aorta. The experiments have shown the feasibility of the approach.

**Keywords:** image segmentation, active contour, image analysis, aortic aneurysm, medical imaging

## 1. INTRODUCTION

Modern medical imaging equipment is capable of producing huge amounts of data per patient. For instance one average CT scan of abdominal region of the human body consists of over a hundred images each of which is $512 \times 512$, 12 bit depth. While this is good from the diagnostic point of view because it provides medical doctors with very precise and detailed information about patient, it on the other hand also introduces problems because this quantity of data is very difficult to handle and analyze. In particular, medical image analysis[1,2] is a challenging task, since it requires design of intelligent artificial systems capable of recognizing and interpreting the structure of a medical image.

In a disease such as abdominal aortic aneurysm[3] it is necessary to asses the condition of aorta in order to plan treatment. Diagnostic procedure in such cases includes taking CT scan of the abdominal region. After the images are obtained it is necessary to determine the location of aorta and to determine the location and thickness of aortic walls. This is also required in order to determine quantitative parameters of the aorta such as volume, diameter, and also to enable qualitative 3-D visualization. To achieve this goal in a more accurate and faster way, it is required to develop appropriate image analysis procedures, of which the most challenging is image segmentation.

One possible approach to the problem of aortic image segmentation is to manually (e.g. using a computer mouse) segment each slice of the CT volume which is an involved and time consuming task. Simple region growing or edge detection methods do not work well because:

1. The aorta is in many places connected with the tissue that has a same optical density.
2. Smaller vessels that branch from the aorta should not be included in segmentation result.
3. The aorta does not have a uniform optical density through the volume.

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It has been shown in practice that often a user assistance is required in more complex image analysis tasks.[4,5] An example of such complex image analysis task is aortic aneurysm segmentation. Because of the above problems we propose a semi-automatic user guided segmentation method based on the active contour approach in which user has to segment only a fraction of the total number of slices and the rest are segmented automatically by the means of the active contour approach. This approach is a trade off between fully manual methods which offer best results but are time consuming and automatic methods which work with minimal interference from the operator but offer less accurate results.

The rest of the paper is organized as follows: In Section 2 the active contour-based segmentation algorithm and our modification which is performed in order to solve our specific segmentation problem is described. In Section 3 experimental results are presented and the conclusion is provided in Section 4.

## 2. SEGMENTATION ALGORITHM

A segmentation approach that is used in this work consists of the two main phases:

1. Manual segmentation of a couple of image slices.
2. Active contour-based automatic segmentation.

The details of the aortic image analysis technique are provided in the following text.

### 2.1. Active border algorithm

Active border is an extension of the active contour in 3-D space. Objects in 2-D space (image) are bounded by 1-D curve while objects in the 3-D space (volume) are bounded by 2-D border. In 3-D active border paradigm the algorithm attempts to minimize an energy function, which is:

1. a function of the optical density of the voxels on which the border is positioned
2. a function of the shape of the border

A good overview of the applications of the deformable model paradigm to medical image analysis can be found in McInerney.[6]

If border $C$ is defined by its parametric description[7]:

$$C(s,r) = [X(s,r), Y(s,r), Z(s,r)]^T, 0 \le s \le 1, 0 \le r \le 1 \tag{1}$$

Then the energy function can be defined to consist of two terms:

$$E(C) = S(C) + P(C) \tag{2}$$

Here, $S(C)$ is the external energy term which is a function of the volume data. This term relates deformable border to the image volume. The second term $P(C)$ represents the internal energy which is a function of the shape of the border. If some energy function $V(x,y,z)$ is defined on entire volume then $S(C)$ can be defined as:

$$S(C) = \int_0^1 \int_0^1 V\left(C\left(s,r\right)\right) dsdr \tag{3}$$

This energy function $V(x,y,z)$ should be formed in such a way to have low values for voxels that are likely to be border voxels of the desired structure. The second term in the energy function $P(C)$ is a function of the shape of the border. This term ensures that the border is continuous and smooth. It can be defined as:

$$P(C) = \int_0^1 \int_0^1 \omega_{01} \left|\frac{\partial C}{\partial s}\right|^2 + \omega_{10} \left|\frac{\partial C}{\partial r}\right|^2 + 2\omega_{11} \left|\frac{\partial^2 C}{\partial s \partial r}\right|^2 + \omega_{02} \left|\frac{\partial^2 C}{\partial s^2}\right|^2 + \omega_{20} \left|\frac{\partial^2 C}{\partial r^2}\right|^2 dsdr \tag{4}$$

where $\omega_{01}, \omega_{10}, \omega_{11}, \omega_{02}, \omega_{20}$ are weight factors. A contour $C$ that minimizes $E(C)$ can be found by solving the following motion equation:

$$\frac{\partial C}{\partial t} - \frac{\partial}{\partial s}\left(\omega_{01}\frac{\partial C}{\partial s}\right) - \frac{\partial}{\partial r}\left(\omega_{10}\frac{\partial C}{\partial r}\right) + 2\frac{\partial^2}{\partial s \partial r}\left(\omega_{11}\frac{\partial^2 C}{\partial s \partial r}\right) + \frac{\partial^2}{\partial s^2}\left(\omega_{02}\frac{\partial^2 C}{\partial s^2}\right) + \frac{\partial^2}{\partial r^2}\left(\omega_{20}\frac{\partial^2 C}{\partial r^2}\right) = F(C) \tag{5}$$

where $F(C)$ is force which is obtained from normalized gradient of external energy term $S(C)$. Additional forces can be added to $F(C)$ to make active contour behave in a certain way. A common choice is an inflation force in border point $C(s,r)$ which has direction of the normal on the border in that point. This additional force ensures expansion of the active border in regions of the volume where volume generated forces are low.

## 2.2. Numerical solution

In order to solve Equation 5 on a digital computer the equation has to be discretized. For this purpose, an additional simplification can be made. If we set $Z(s,r) = r$ in Equation (1) our 3-D border reduces to a sequence of 2-D curves. In this manner we can disable movement of the border nodes between the slices. In addition, there is no force in $z$ direction. In this case the discretized version of contour $C$ can be written as:

$$C(s,z) = [X(s,z), Y(s,z), z]^T, s \in \{s_0, s_1, \ldots, s_{m-1}\}, z \in \{z_0, z_1, \ldots, z_{n-1}\} \tag{6}$$

where $m$ is the number of discretization points (nodes) for one curve which is the same for all of the curves and $n$ is the number of cross-sections. After discretization of Equation (5) using the finite difference approximation, and separating equations for $X$ and $Y$ coordinates we obtain the following discrete equations[8]:

$$X^n = (I + \tau A)^{-1}[X^{n-1} + \tau F_x(C^{n-1})] \tag{7}$$
$$Y^n = (I + \tau A)^{-1}[Y^{n-1} + \tau F_y(C^{n-1})] \tag{8}$$

where $\tau$ is the discretization step. If $\tau A$ is small enough we can approximate the matrix expression $(I + \tau A)^{-1}$ by $(I - \tau A)$. This matrix is banded and multiplication of discretized border coordinate points $X$ or $Y$ with it is equal to the convolution by a $5 \times 5$ smoothing kernel. As additional simplification, this kernel can be decomposed into two 1-D kernels, one for smoothing in a single curve and other for smoothing among curves. If we set $\omega_{01} = \omega_{02} = k_1, \omega_{10} = \omega_{20} = k_2$ and $\tau = 1$ then these kernels are defined as:

$$H_1 = [-k_1, 5k_1, 1 - 8k_1, 5k_1, -k_1] \tag{9}$$

and

$$H_2 = [-k_2, 5k_2, 1 - 8k_2, 5k_2, -k_2]^T \tag{10}$$

Note that this separation is possible only with $\omega_{11} = 0$. If $\tau$ is set to 1 then we must choose small $k_1$ and $k_2$ constants to obtain good numerical stability. Kernel $H_1$ smoothes the points lying in the curve in one plane and $H_2$ smoothes in $z$ direction (among curves).

The forces are calculated as normalized spatial derivatives of the external energy function:

$$F_x = -k_f \frac{V^x}{|V^x| + |V^y| + \varepsilon} \tag{11}$$

$$F_y = -k_f \frac{V^y}{|V^x| + |V^y| + \varepsilon} \tag{12}$$

where $V^x$ and $V^y$ are derivatives of $V$ in $x$ and $y$ directions respectively, $k_f$ is a force constant and $\varepsilon$ is some small numerical constant which ensures that there is no division by zero in Equations 11 and 12. Given the above equations the algorithm which evolves active border is summarized in the following algorithm.

**Algorithm 1** The active border evaluation algorithm.

1. **REPEAT**
2. Apply forces described in Equations (11) and (12) to each border node.
3. Smooth the border using kernels $H_1$ and $H_2$
4. **UNTIL** there is no significant decrease in overall energy

### 2.3. Implementation details

In order to use the motion equations it is necessary to determine the initial border $C^0$ and the external energy function $V(x, y, z)$. This choice is application specific and in this subsection we describe the details of our implementation for aortic aneurysm segmentation.

The initial border is determined in the following way. The user manually (using a computer pointing device) initializes 2-D contours for some number of values of parameter $z$. For the remaining slices the initial contours are linearly interpolated. To avoid the problems with contour extrapolation the first contour $C(s, z_0)$ and the last contour $C(s, z_{n-1})$ have to be manually initialized. Furthermore, it must be noted that the number of contours is usually large and the shape of the border significantly varies across the cross-sections. If only these two contours were manually initialized that would result in a poor initialization for most of the cross-sections. In order to avoid this the problem user is required to initialize additional number of contours between 0 and $n - 1$. Of course, it is necessary to find the optimal trade-off between the segmentation accuracy and the necessary user interaction which both increase with the number of manually segmented curves.

The energy function $V(x, y, z)$ is calculated from the gradient of the original volume $I(x, y, z)$. The gradient is calculated as follows:

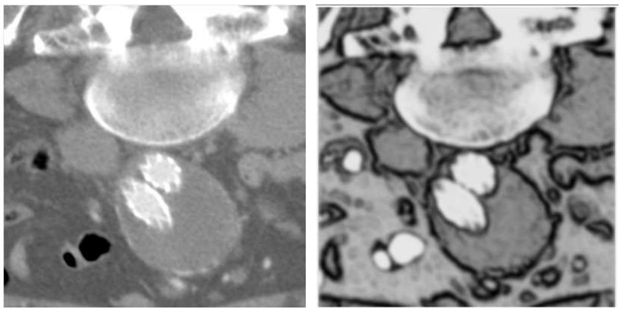
$$D = |\nabla G_{\sigma_1} \bullet I| \tag{13}$$

where $\nabla G_{\sigma_1}$ is the directional derivative of the 2-D Gaussian kernel with standard deviation $\sigma_1$, and $\bullet$ denotes the 2-D convolution operation. 3-D kernel is not used since the node points can not move among cross sections (in $z$ dimension) so there is no need for calculating forces in $z$ direction. The energy function is calculated from the gradient for each cross-section separately. This is done because the borders of our region of interest have different values of gradient for different cross-sections due to different tissue on the border of the region. For each of the manually segmented slices $z$ mean value and standard deviation of the gradient ($mg_z$ and $sg_z$) and of the optical density ($md_z$ and $sd_z$) are calculated on the borders. Since these border points are manually drawn, instead of the gradient value at the border point $(x, y)$ in cross-section $z$ the maximum value in a $3 \times 3$ neighborhood is used and for optical density the median value in same neighborhood is used. For slices which are not manually segmented mean and standard deviation values are linearly interpolated. The energy is then formulated in the following way:

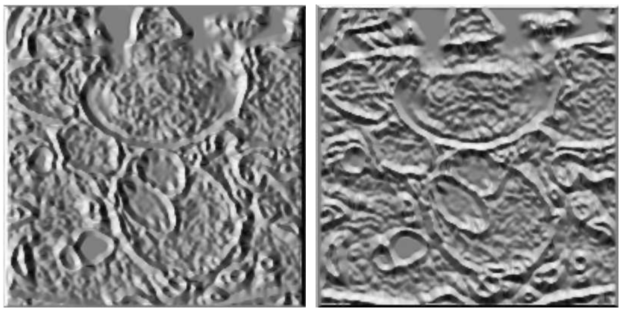
$$V(x, y, z) = -G_{\sigma_2} \bullet \exp\left(-\left(\frac{D(x, y, z) - mg_z}{c_1 sg_z}\right)^2 - \left(\frac{I(x, y, z) - md_z}{c_2 sd_z}\right)^2\right) \tag{14}$$

The constants $c_1$ and $c_2$ are here to evaluate importance of the gradient $D$ and the optical density $I$, respectively. The energy is smoothed by 2-D Gaussian kernel with standard deviation $\sigma_2$. Note that the kernels in Equations (13) and (14) both can be decomposed in two 1-D kernels which speeds up evaluation of the above equations.[9] The energy calculated in this way is in the range $-1 \dots 0$ so no normalization is necessary. The energy function formulated in this way utilizes the information from manually segmented slices which is improvement over more general approach, and also makes it less sensitive to the absolute value of the border gradient.

An example of abdominal CT slice, its energy function and derived forces are shown in the Fig. 1. This is extracted region from the CT slice zoomed two times around aorta region. In the energy image bright pixels have high and dark pixels low energy value. In the force images, voxels with high value of the force in the direction left $\rightarrow$ right (for image with force in $x$ direction) and in the direction top $\rightarrow$ bottom (for image with force in $y$ direction) are bright. The voxels with force in the opposite direction are dark. The voxels with a small value of the force are gray.



(a) Zoomed region from the original CT slice　　(b) Energy function



(c) Forces in $x$ *direction*　　(d) Forces in $y$ *direction*

**Figure 1.** Original CT slice and the derived energy and forces

Since during evaluation of the algorithm positions of the nodes are not integer values evaluation of force functions $F_x$ and $F_y$ at sub pixel accuracy is necessary. We used bilinear interpolation for this task. Since contours in manually edited slices are correct, equations of motion are not applied to nodes in those contours, so these contours stay in fixed positions.

## 3. EXPERIMENTAL RESULTS

A computer program that implements the described algorithm was developed. The program has been tested in the clinical environment on the real patient abdominal CT data. Segmentation was performed on the manually selected region of interest extracted from the original CT volume. The dimensions of the region are usually around 200 voxels in $x$ and $y$ directions and 100 voxels in $z$ direction. Values of the numerical constants needed in the algorithm were set to the following values: Constants $k_1$ and $k_2$ which determine smoothness of the border were both set to 0.03. A larger value would over-smooth borders and some details would be lost while a smaller value would cause active border to include some small structures lying near the aorta in some cross-sections. Constants $c_1$ and $c_2$ in Equation 14 are set to 2.0 and 3.0, respectively. The force constant $k_f$ was set to 1.5. Gaussian and derived Gaussian kernels are of dimension $7 \times 7$ and have standard deviation $\sigma = 2.0$. The number of node points $m$ for each of 2-D curves was set to 50. The following stopping criteria is used. The algorithm stops if:

$$0 \geq E^n - \text{mean}\left(E^{n-k}, \ldots, E^{n-1}\right) \leq c_s \tag{15}$$

where $E^n$ is the external energy of the border $C^n$ normalized per one border node, $k = 8$, and$c_s = 0.002$.

The graphical user interface is shown in the Fig. 2. In the user interface user can segment cross-sections manually and after that he can start automatic segmentation. After the segmentation user can adjust cross-sections which are not correctly segmented.

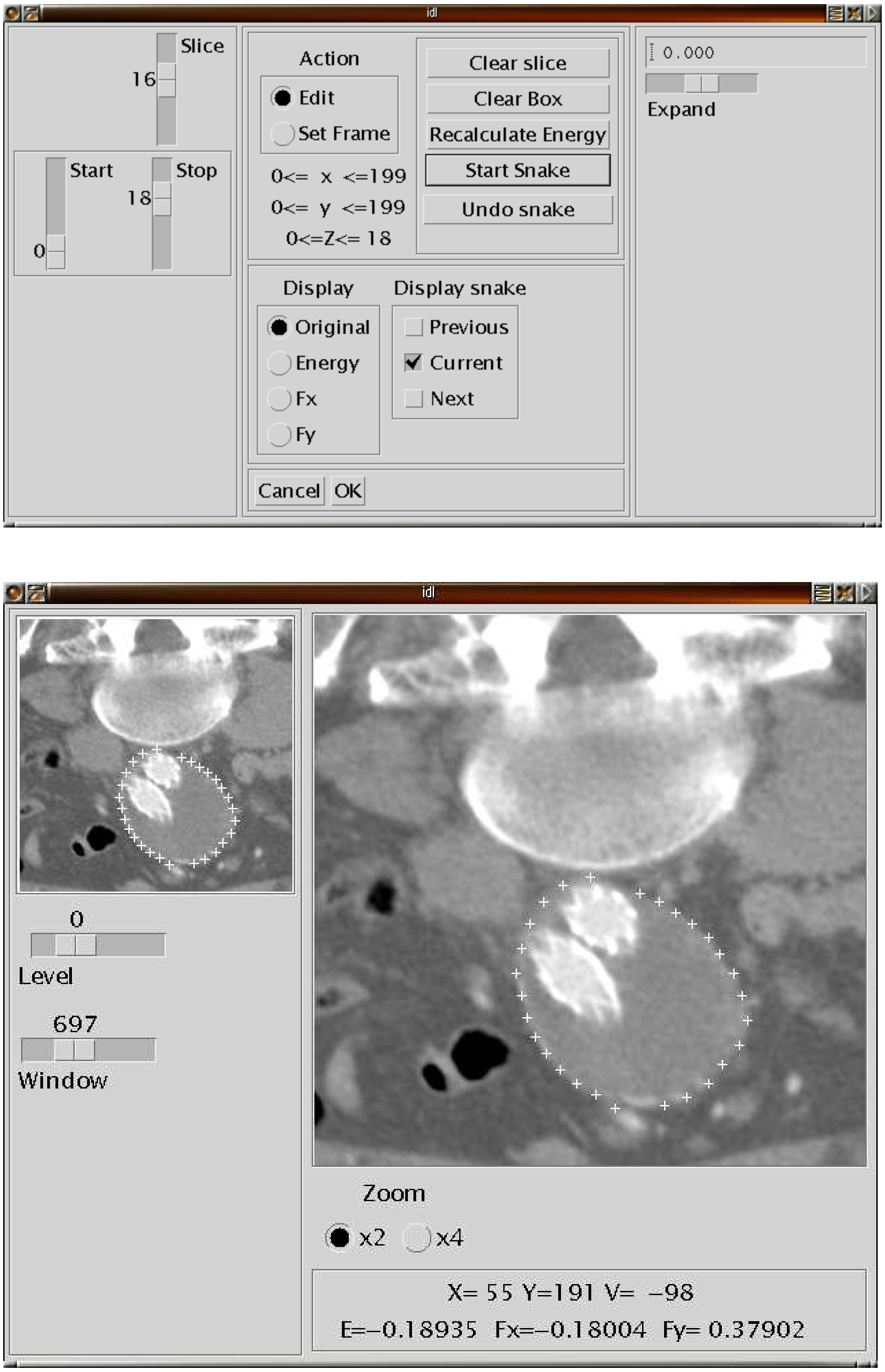
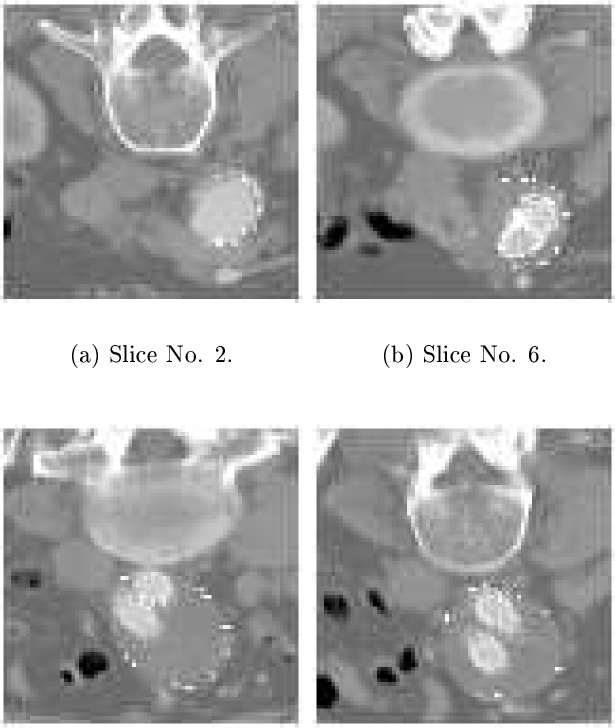



**Figure 2.** The graphical user interface for the proposed algorithm



(a) Slice No. 2. (b) Slice No. 6.

(c) Slice No. 11. (d) Slice No. 18.

**Figure 3.** The results for four different cross sections from one patient.

The computer program has been developed in the IDL programming environment which makes it platform independent. The program has been tested on SGI Indigo 2, SUN Ultra 1, and Pentium-based PC workstations.

The results for four different cross sections from one patient are shown in Figure 3. In this case volume had 27 slices and each cross-section was $200x200$ voxels. Slices number $1, 9, 18$, and 27 are manually edited.

## 4. CONCLUSION

In this work a method for user-assisted (semi-automatic) segmentation of CT volumes of abdominal region of the human body is presented. The user (e.g. a radiologist) has to manually segment a fraction of total cross-sections in the CT volume, while other cross-sections are segmented automatically. The algorithm used for automatic segmentation is a simplified 3-D deformable contour algorithm. Application specific energy function has been used which utilized information in the volume data and also provided by user by manual segmentation. The energy function is fine-tuned for the specific task of segmentation of aortic aneurysm region from CT scans of abdominal region of the human body. With other choice of energy function parameters it can be used for different volume segmentation tasks.

The advantage of this approach to the manual segmentation is that the number of slices that the user has to segment can be significantly reduced. Fully automatic approach is not used because it is less reliable, especially in atypical cases. The method has been tested in clinical environment and has shown good results.

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