Deformable Contour Based Method For Medical Image Segmentation

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Abstract: *In this paper we present a method for segmentation of medical images based on a deformable contour paradigm. The deformable contour is a novel approach in image segmentation and has some advantages over classical segmentation methods such as region based or edge mased methods. We are using the level set inplementation of the deformable contour paradigm. The graphical user interface for the algorithm is also developed. Images we are segmenting are computed tomography (CT) scans of the abdominal region of the human body and our region of interest is aorta (blood vessel). For one of the volumes results are visualized in 3-D.*

Keywords: image segmentation, active contour, computed tomography

1. Introduction

In this work we present a method for segmentation of computer tomography (CT) images of the human abdominal region. Typical CT image is shown in Figure 1. Data set for each patient consists of forty to fifty such images taken with different values of height coordinate so all images together represent volume data of the patient abdominal region. The object of interest in this volume is aorta which is an important blood vessel (marked with arrow in Figure 1).

The aorta consists of two parts: the perfused and the unperfused part. Blood flows only through perfused part. If it necessary to measure aorta parameters, such as minimal radius, volume, or to visualize the whole volume, it is required to segment aorta in whole data set which is time consuming and cumbersome task when it is done manually. Manual segmentation involves manual outlining of aorta contours in every slice.

The idea of this work is to provide some assistance to radiologists so that they only have to segment a few of the slices manually and the rest should be done automatically. We present a method for automatic segmentation which is based on a deformable model.[5]

The rest of the work is organized as follows: In the second section the active contour paradigm for image segmentation and our implementation of it are described. In the third section implementation details and results are given, and in the last section the conclusion is provided.

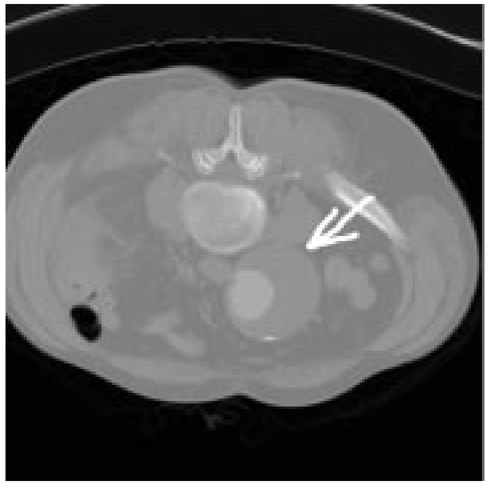

Figure 1. CT scan of abdominal region. Aorta is marked by arrow

2. Segmentation algorithm

Segmentation methods are usually divided into two region-based and edge-based methods.[1] In region-based methods an algorithm usually searches for connected regions of pixels with some similar feature such as brightness, texture pattern, etc. These algorithms work in the following way: The first image is in some way divided into regions. Then for each region similarity among pixels is checked. If similarity is below some threshold, region is divided into smaller regions. In the next step neighboring regions with similar features are merged into a new bigger region. These two steps are repeated until there is no more splitting or merging. The problem in this approach is to determine exact borders of objects because regions are not necessary split on natural borders of the object.

Alternative approach is edge-based. In this approach an algorithm searches for pixels with high gradient value which are usually edge pixels and then tries to connect them to form a curve which represents a boundary of the object. A difficult problem here is how to connect high gradient pixels because in real images they are usually not neighbors. Another problem is noise. Since a gradient operator is of a high pass nature, and the noise is usually also in high frequencies it can sometimes create false edge pixels.

Active contour approach[3] is a method for image segmentation which tries to combine good features of both global and local methods. In this approach a deformable closed contour is positioned on the image and then deformed and moved in such a way that it is positioned on the border of the region we want to segment at the end of the process. This contour can be represented as:

$$v(s,t) = (x(s,t), y(s,t))^T \tag{1}$$

where x and y are coordinates and s is parametric domain $s \in [0,1]$. The contour evolves from $t = 0$ to $t = T_{max}$ which is the final contour and the result of segmentation process. The contour is deformed in such a way to minimize energy functional

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

Here $S(v)$ represents deformation (internal) and $P(v)$represents positional (external) energy. $S(v)$ is given by:

$$S(v) = \int_0^1 \left(\omega_1 \left| \frac{\partial v}{\partial s} \right|^2 + \omega_2 \left| \frac{\partial^2 v}{\partial s^2} \right|^2 \right) ds \tag{3}$$

$S(v)$ describes deformation of elastic body where ω_1 is tension (resistance to stretching) and ω_2 is rigidity (resistance to bending). The second term $P(v)$ connects contour to the image and it is given by:

$$P(v) = \int_0^1 P(v(s))ds \tag{4}$$

$P(x, y)$ is a scalar potential function of image pixels. In our case we are searching for the edge pixels, and since they have high gradient value it is formulated as:

$$P(x, y) = \exp(-\|\nabla G_\sigma * I(x, y)\|) \tag{5}$$

where $I(x, y)$ is the grayscale image and ∇G_σ is a Gaussian filter. These two terms impose global and local constraints on the contour. $S(v)$ imposes global constraints on the contour. It has to be closed and smooth. Smoothness can be adjusted by adjusting ω_1, and ω_2. $P(v)$ imposes local constraints on contour position: it has to be positioned on pixels with high gradient, usually the edge pixels. This solves problems of standard edge-based methods, since the contour is already connected and there is no need to connect isolated pixels, also if there are some pixels corrupted with noise they are usually isolated and contour would not get stuck in them because that would significantly increase $S(v)$ (contour would have broken shape). On the other hand problems with exact position of the border which exist in region based methods are also solved by introducing $P(v)$ because if contour is not positioned on high gradient pixels border $P(v)$ has high value.

In our work we use the level set implementation[4] of active contour paradigm in which contour $v(s, t)$ is represented as the level set of the higher dimensional surface Ψ which is defined on the whole image plane in the following way:

$$\Psi(x, y, t) = \pm d \tag{6}$$

where d is a distance from point (x, y) to active contour v at time t. d has a positive sign if point is outside contour and negative sign otherwise. In this approach the active contour at time t is described as set points (x, y) so that $\Psi(x, y, t) = 0$. Equation of motion as derived in[2] which ensures evolution of level set function and convergention to a stable solution is given by:

$$\frac{\partial \Psi}{\partial t} = P\|\nabla\Psi\| \left(div \left(\frac{\nabla\Psi}{\|\nabla\Psi\|} \right) + \nu \right) + \nabla P \cdot \nabla\Psi \tag{7}$$

In this equation additional term ν id added to ensure expansion of the active contour on the regions with low gradient. Note that there is no $S(v)$ term in this equation. This energy term is implicit in level set method. For details see.[2] To solve this equation on a digital computer it has to be discretized. Discretization is performed as described in.[4]

for i=1 , . . . , n **do**
  Calculate G_i from I_i as described in Equation 5.
end for
for i=1 , . . . , n **do**
  Calculate T_i using Equation 8.
  Initialize V_i as small circle with center at T_i
  Construct Ψ from V_i using Equation 6.
  Evolve Ψ according to Equation 7.
  Extract V_i from Ψ as described.
  Calculate C_i from V_i
end for

Figure 2. The segmentation algorithm.

Since it is necessary to initialize active contour inside object we are trying to segment we use the following procedure for initialization of each slice. For the first slice operator has to pick a starting point $T_1(x, y)$ using a developed graphical user interface(GUI) (shown in Figure 3). Initial active contour for this slice is a circle with small radius and a center at T_1. For each following slice n the center of the initial contour is calculated using the following formula:

$$T_n = 2C_{n-1} - C_{n-2} \tag{8}$$

Where C_n is the center of the gravity of the evolved active contour in the slice n, with C_0 set to be equal to C_1. The procedure is repeated for all slices. The segmentation algorithm is shown in Figure 2. The input are N CT images $I_n(x, y)$, $n \in [1 \ldots N]$ and the initial point in the first slice T_1. The output are N border contours V_n, $n \in [1 \ldots N]$.

3. Implementation and results

In this section implementation details and results are presented. Segmentation software is developed in C programming language under Unix / X windows environment. The software is divided into two components: segmentation algorithms and graphical user interface. They are separated to reduce dependency of the implementation to specific platform (in our case Solaris 2.6 is used). Module with implementation of algorithms is developed in the form of dynamic link library and is written in ANSI C. This enables cross platform compatibility. GUI is developed using Xlib/Motif. The GUI is shown in Figure 3. Since aorta consists of perfused and unperfused regions segmentation has to be done separately for both of these regions. Evolution of the active contour for the unperfused part is shown in Figure 4. On the left is initial snake contour, in the middle is contour after 300 iterations and on the right is contour after it has reached a stable state. 3-D visualization of results for one case is shown in Figure 5. The perfused part is shown as darker and the unperfused part as brighter volume. The surface rendering is done using a rendering software package called Visualization Toolkit (VTK).[6] The algorithm used for volume edge is marching cubes.

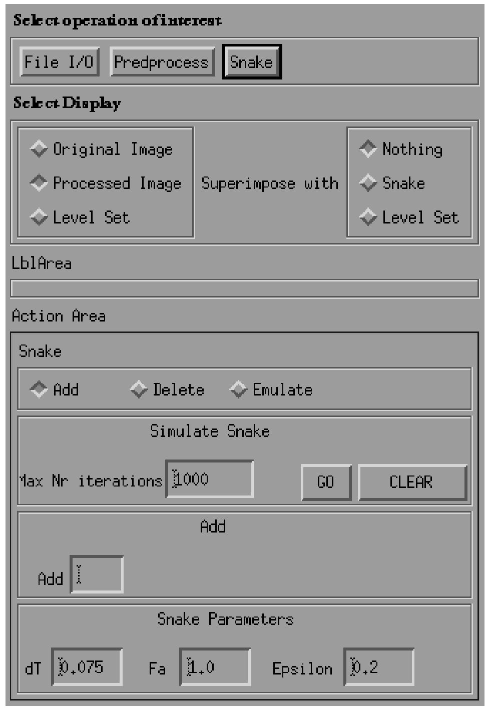

Figure 3. Graphical user interface for the proposed algorithm developed under X windows environment

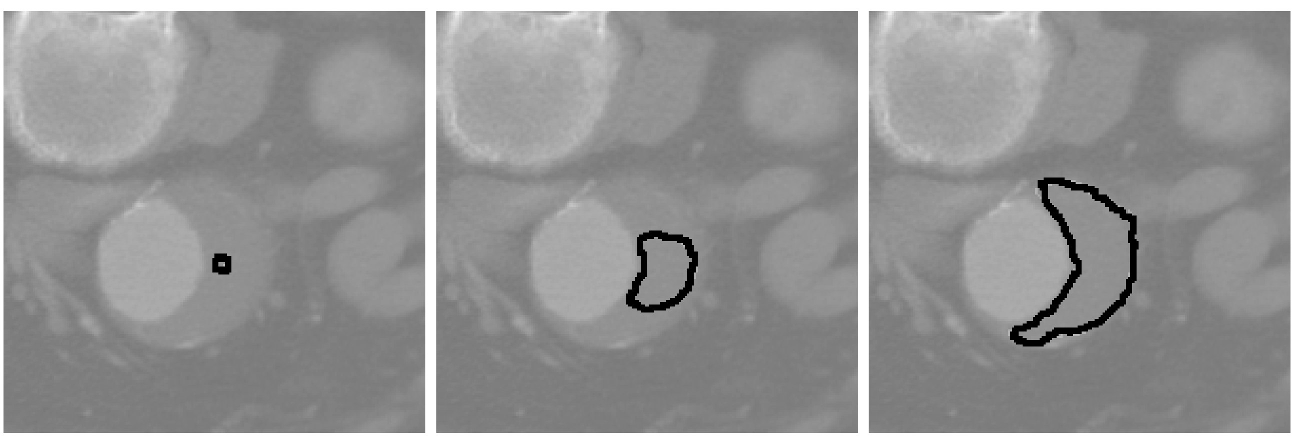

Figure 4. Segmentation of the unperfused part of the blood vessel. Initial contour (left), after 300 iterations(middle) and final result(right).

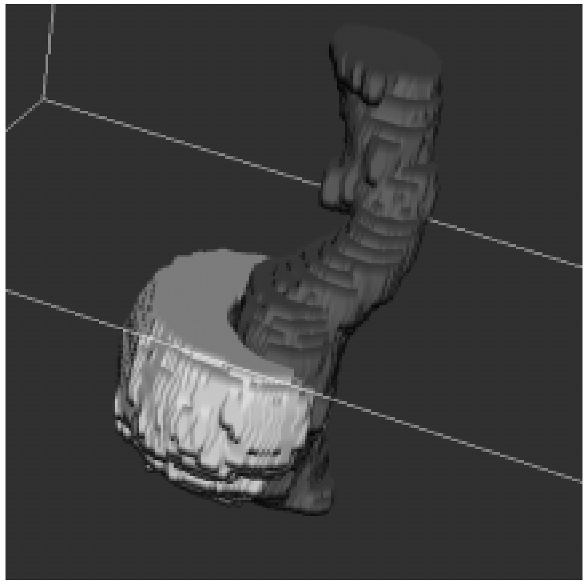

Figure 5. 3-D visualization of the segmented volume in VTK

4. Conclusion

In this work a deformable contour based method for image segmentation of medical CT images of the abdominal region of human body is presented. The method is based on a level set implementatiom of the active contour algorithm with automatical determination of the original position of the active contour.

This method is introduced to overcome shortcomings of standard edge or region based methods. Since data set consists of multiple images a method for initializing active contour in consecutive images is introduced. Results obtained by this method are good and the method offers significant help to radiologists who need to analyze a set of CT images.

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