

Recognition and Segmentation of Digestive System Focus Based on Two Parametric Active Contour Models

Wan Yi^{1, a}

¹Sichuan University of Science & Engineering, Zigong, Sichuan 643000, China.

^aEmail: amigowan@163.com

Abstract

In this study, we use Snake model and discrete dynamic contour algorithm based on parametric active contour model to recognize, segment and mark the focus tissue in the digestive tract, and verify the effectiveness, advantages and limitations of the two algorithms through comparative experiments.

Keywords

Parametric Active Contour Model, Digestive system focus, Snake model, Discrete dynamic contour algorithm.

1. Introduction

The diameter of our digestive tract is not regular, and it has certain flexibility and smoothness. In the endoscopic diagnosis and treatment technology, the small driving equipment used needs to be processed accurately according to the real-time image data, and depending on the real environment or the target tissue status of the lumen, actively and adaptively lock the damaged part of the lumen, flexibly drive the inspection equipment to reduce the blindness of operation, and reduce the patient's body injury caused by the difficulty of operation or other subjective factors. And the focus tissue image in the lumen is segmented and extracted. We use Snake model based on parametric active contour model and discrete dynamic contour algorithm to recognize, segment and mark the lesions in the lumen. At the same time, the effectiveness, advantages and limitations of the two algorithms are verified by comparative experiments.

2. The principle of Snake Model Segmentation Algorithm

We call the model first proposed by M. Kass, A. Witkin and D. Terzopoulos as the traditional Snake model [1] [2], which is a relatively simple Snake model. Its core idea is to get an energy minimum functional by limiting the boundary characteristics of the target, and to get the segmentation image by the curve evolution. In the Snake model, the requirement of boundary extraction is changed to the requirement of energy minimization. Snake is defined as a changing curve under the influence of internal and external forces.

A parametric curve $C(s, t) = [x(s, t), y(s, t)]$ is defined, in which $s \in [0, 1]$ is the normalized parameter, and Snake model can be expressed as the mapping of the curve to the image. Assuming that the image to be segmented is $I(x, y)$, according to the contour evolution theory, Snake evolves on the whole image plane Ω , and its minimum energy function is:

$$J(C) = \int_{\Omega} (E_{\text{int}}(C) + E_{\text{ext}}(C)) ds \quad (1)$$

The energy function includes internal energy E_{int} and external energy E_{ext} . The high-level shape information is processed by internal energy. The external energy represents the low-level information of the image, generally the edge and so on. The internal energy E_{int} controls the elastic energy and bending energy of the contour line by adjusting parameters:

$$E_{\text{int}} = \frac{1}{2} \left(\alpha |C'(s)|^2 + \beta |C''(s)|^2 \right) \quad (2)$$

Among them, α and β are artificially set control parameters, and the smoothness and continuity of the curve are controlled by them, which are the first and second derivative respectively. The details can be obtained by the following equation. $C'(s)$, $C''(s)$ are the first and second derivatives of $C(s)$, which can be obtained from the following formula:

$$C'(s) \Big|_{C=C_i}^2 = \|C_i - C_{i-1}\|^2 = (x_i - x_{i-1})^2 + (y_i - y_{i-1})^2 \quad (3)$$

$$C''(s) \Big|_{C=C_i}^2 = \|C_{i+1} - 2C_i + C_{i-1}\|^2 = (x_{i+1} - 2x_i + x_{i-1})^2 + (y_{i+1} - 2y_i + y_{i-1})^2 \quad (4)$$

Where C_i , $i = 1, 2, \dots, n$ is the points on the curve.

The external energy E_{ext} is a scalar function defined on the global image $I(x, y)$, which can represent the individual characteristics of the image, such as the boundary and so on. The more concise E_{ext} is as follows:

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

Because the definition of the external energy function is the inverse of the gradient of the image, the external energy of the boundary point of the image is the smallest. In a clear image, minimizing the external energy function E_{ext} can make the contour line be attracted to the target edge. A common external energy function is:

$$E_{\text{ext}}(x, y) = -|\nabla(G_\sigma(x, y) * I(x, y))|^2 \quad (6)$$

Among them, $G_\sigma(x, y)$ is a two-dimensional Gaussian function whose mean value is zero, variance is σ , ∇ is gradient operator, and $*$ is convolution operation. The denoising effect is obtained by convoluting the image with two-dimensional Gaussian function. The potential energy function defined by equation (2-6) is called edge map of image.

As mentioned above, the traditional Snake model belongs to the parametric dynamic contour model. By using the Lagrangian method, the Snake of the minimization formula (2-1) must meet the following Euler equation:

$$\alpha C''(s) - \beta C^{(4)}(s) - \nabla E_{\text{ext}} = 0 \quad (7)$$

The above equation can be regarded as a balance equation:

$$F_{\text{int}} + F_{\text{ext}} = 0 \quad (8)$$

However, $F_{\text{int}} = \alpha C''(s) - \beta C^{(4)}(s)$ and $F_{\text{ext}} = -\nabla E_{\text{ext}}$ are internal and external forces. The extension and contraction of the curve are controlled by F_{int} , and F_{ext} makes the curve move towards the target edge. Taking $C(s)$ as a function of time $F_{\text{int}} = \alpha C''(s) - \beta C^{(4)}(s)$ and unit parameter $F_{\text{ext}} = -\nabla E_{\text{ext}}$, the iterative formula of contour line is obtained

$$C(s, t+1) = C(s, t) + \alpha C''(s, t) - \beta C^{(4)}(s, t) - \nabla E_{\text{ext}} \quad (9)$$

Solve according to discretization,

$$x^n = (A + \mathcal{H})^{-1} (x^{n-1} - F_x(x^{n-1}, y^{n-1})) \quad (10)$$

$$y^n = (A + \mathcal{H})^{-1} (y^{n-1} - F_y(x^{n-1}, y^{n-1})) \quad (11)$$

x^n is the nth iteration result of X , $\mathcal{H}$ is the step parameter, A is the matrix attached to α and β , F_x and F_y are the finite difference approximation of derivatives, and (x, y) are the points on Snake. Specific implementation process: first set an initial contour manually or according to other mechanisms, and then iterate step by step according to the above formula until a satisfactory segmentation result is obtained. The number of iterations can be set in advance, or the suspension conditions of iterations can be set in advance. If the range of motion of the curve does not exceed a certain closed value in the set two adjacent iterations, once the result of the iteration meets the end condition, it is considered that the contour has converged to the minimum of the external energy function, and the final segmentation result is obtained.

3. Principle of Discrete Dynamic Contour Algorithm

DDC (discrete dynamic contour algorithm), an energy-based model, is composed of some control points. For example, the edge line of a contour can be controlled by N control points. To calculate the reproduction, collision, contraction and deformation of the whole contour is to calculate the positions of these control points at different times. Although there is a straight line between these points, through deformation and increasing the number of sampling points, it can become a more precise and smooth description.

3.1. Composition of Forces in Discrete Dynamic Contour Algorithm

In the two-dimensional coordinate system, specify any point I , at any time T , the coordinate can be described by the formula:

$$p_i(t) = \{x_i(t), y_i(t)\} \quad (12)$$

Here, $x_i(t)$ and $y_i(t)$ take time t as the variable X coordinate and Y coordinate position, and the current position of $p_i(t)$ at which they work together can be described by the force at this position of the point. These forces are all vectors. Every point i is called vertex. Its total forces are the total forces acting on this point. We divide the overall force into three parts:

$$f_i^{tot}(t) = w^{im} f_i^{im}(t) + w^{in} f_i^{in}(t) + w^d f_i^d(t) \quad (13)$$

The first part of the force is called $f_i^{im}(t)$. Image force is driving this point to the feature (the edge position to be reached eventually). The force is multidirectional, which can expand outwards and contract inwards. The second part of the force, called $f_i^{in}(t)$, contour force refers to the internal force, which makes the whole contour not move too fast when it is deformed, so as to ensure that the change between each point can reach a smooth state. Contour Force avoids the following situation: if one point in the initial contour moves quickly and the other points do not move, the top state will appear. Internal force will promote all points to be evenly distributed, and there is some interaction between them, so that they can expand outwards or contract inwards evenly. The third part of the force is called $f_i^d(t)$. The main purpose of stamping force is to reproduce the whole edge. In the process of deformation, the oscillation caused by the first two forces can be effectively removed, and the deformation process is very stable.

The whole formula consists of three parts of forces, each of which has a weight W . If the total force acts on any vertex i , according to the change of time axis, an acceleration will be generated at this point. Acceleration is related to mass and defined by the following formula. Acceleration is also a vector:

$$a_i(t) = \frac{1}{m} f_i^{tot}(t) \quad (14)$$

In this formula, m is the mass of any point. In the whole calculation process, the mass of any point is basically not considered, so it is set as $M = 1$. The speed $v_i(t) = (t + \Delta t)$ of $t + \Delta t$ at the next moment, the speed $v_i(t)$ of t at the last moment, plus its acceleration times its time change. And speed is also a vector.

$$v_i(t + \Delta t) = v_i(t) + a_i(t) \Delta t \quad (15)$$

So the position $p_i(t + \Delta t)$ of the next moment is equal to its position $p_i(t)$ of the previous moment, plus the speed times its time difference. After several iterations, we can get the position of the later time.

$$p_i(t + \Delta t) = p_i(t) + v_i(t) \Delta t \quad (16)$$

3.2. Explanation of Force in Discrete Dynamic Contour Algorithm

Here are the explanations for these three forces:

1. Image force, described by the following mathematical model:

$$f_i^{im}(t) = -\nabla E(x_i, y_i) \quad (17)$$

Image force will drive vertex to approach the final boundary. From the view of image energy, we define the model according to the property that the height is inversely proportional to the speed in the physical field. If a car is at a very high altitude, its potential energy will be very high, and its kinetic energy will be very small. When the car comes down from the mountain, its potential energy will be converted into kinetic energy. In a lower place, the speed will be very fast, and the potential energy will be reduced.)

It is the same in the image: describe the whole gray range of the image as having gray level difference, define the high place as the potential energy is relatively high, and define the low place as the potential energy is relatively low. If this point is in the place with relatively high gray value, it will go to the place with relatively low gray value. The change of image energy refers to the change of image gray, through which the force of changing image is formed. E is called energy of image, which is a gradient value model. For each vertex, its position in the middle of image and its energy are calculated. The following fraction model can be used to describe energy:

$$E(x_i, y_i) = \frac{1}{\|\nabla(G_\sigma * I(x_i, y_i))\| + 1} \quad (18)$$

For image pixel $I(x_i, y_i)$, find its Gaussian smoothing $G_\sigma * I(x_i, y_i)$, then its gradient, and then its modulus (its numerical part). Add 1 in the formula because this value is the denominator, so a very small constant should be added to avoid the situation that the denominator is 0. The purpose of smoothing the image with two-dimensional Gaussian filter is to remove the very small local minima, so that the gradient will be more gentle and the convergence process will not fall into the local minimum. Gradient of pixels is to determine whether $I(x_i, y_i)$ is on the edge of the image. For the design of this energy model, if $I(x_i, y_i)$ is not at the edge of the image, the pixel gradient is small, and the energy is large; if $I(x_i, y_i)$ is at the edge of the image, the pixel gradient is large, and the energy is small.

For the whole image, the force is related to the change of image energy. In the flatter region, the smoother the image, the stronger the point motion. The larger the gradient transform, the smaller the image force, and the easier the point to stop.

2. In order to make the whole contour evolution process, internal force will become very smooth. Therefore, if we want to describe whether an edge is smooth, we have a value of curvature to describe it. When the radian is large, the edge is not smooth; when the radian is small, the edge is relatively smooth. We want to prevent the edge of the outline in the middle of the image from popping out. Internal force will try to reduce this situation in such a way that each position can minimize the local curvature of the minimizing local curvature.

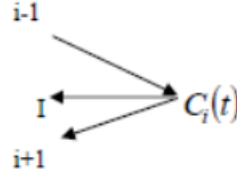
Curvature model described as $C_i(t)$:

$$f_i^{in}(t) = C_i(t) \quad (19)$$

Internal force is expressed by the curvature of this point at time t :

$$C_i(t) = \hat{d}_i(t) - \hat{d}_{i-1}(t) \quad (20)$$

Using this graph, we can see that:



If there are three points $i-1$, i , $i+1$, there will be vectors in two directions. From $i-1$ to i is $\hat{d}_{i-1}(t)$, from i to $i+1$ is $\hat{d}_i(t)$, and an angle will be formed between the two directions. When the angle is smaller, the curvature will be larger; otherwise, if the angle is larger, the curvature will be smaller and relatively smooth. This forms an inverse relationship. When the angle is relatively large, the arrow of $C_i(t)$ will be slightly smaller; otherwise, if the angle is smaller, it will be larger. This force will pull it smooth.

3. Damping force reduces the swing of the first two forces and stops at the end to prevent the points on the whole contour from shaking back and forth and counteract the previous forces. This force is defined by a velocity dependent formula:

$$f_i^d(t) = w^d v_i(t) \quad (21)$$

Where $-1 < w^d < 0$.

4. Resampling. In the process of updating the vertex position, resample the whole deformation contour of DDC. Each vertex calculates the force, velocity and position independently, and its direction of motion can not be controlled. At some time, all the points may move in one direction, which will cause many points to pile up and be too dense, while other contour lines will be very sparse, so some areas will no longer have a little control. Because of the uneven change of density, the algorithm may eventually fail. Based on this consideration, all control points on the whole contour should be resampled after each position deformation. Through linear interpolation, some control points are removed in the too dense area, and some control points are added in the too sparse area, so that it is evenly distributed in the whole edge line. In the next calculation of force, speed and position, it can achieve a very optimized structure.

3.3. Discrete Dynamic Contour Algorithm Steps

The whole algorithm is described as the following steps:

1. Display image;
2. In the system, a profile template, such as a square template, is initially set. For these four vertices, there will be its velocity and acceleration (the initial velocity acceleration is 0), which will change with time;
3. Calculate the total force of each vertex, which has a value at a certain time;
4. Then calculate the acceleration of the vertex, update the position information, calculate the position of the next moment and display;
5. Then update the position and speed changes at any time. At the same time, we need to resample the control points on the whole contour;
6. Resampling DDC (discrete dynamic contour);

7. Repeat steps 3-6 until the velocity and acceleration on the vertex approach 0 (design two very small thresholds to make a decision), or customize an iteration number. End.

Finally, it is concluded that image force is included in total force, and image force is mainly related to the gradient of image. In the flat area with smaller gradient transformation, the larger image force is, the stronger the motion of vertex is. The larger the gradient transformation is, the smaller the image force is, which makes the vertex stop easily. Internal force makes the whole contour more uniform, so that it doesn't have a point to show a sharp state. In addition, in order to prevent jitter and make the whole deformation process stable, we also use damping force. These three forces are multiplied and then added together with their respective weights to form the whole process of total force. In addition, it should be emphasized that the whole contour should be resampled in every step of the deformation process.

4. Multi Focus Image Recognition and Segmentation Based on Two Parametric Active Contour Models

4.1. Image Recognition and Segmentation of Multiple Lesions Based on Snake Model

Compared with the traditional bottom segmentation algorithm, the traditional Snake model has the following advantages [3]:

1) Image information, initial estimation, target contour and knowledge-based constraints are unified in a feature extraction process. 2) After a certain initialization, it can spontaneously converge at the minimum of energy. 3) In scale space, the energy is minimized from coarse to fine, which can greatly increase the capture area and reduce the difficulty of solution.

Because of the defects of the model itself, the traditional Snake model has many disadvantages as follows:

1) The energy functional is dependent on the curve parameters. If there is a difference in the data of the same arc, the results of the functional will also change. 2) Because the force converging to the edge of the target comes from the gradient of the image, and the gradient only exists near the edge of the target, the performance of the traditional Snake model is very sensitive to the initial Snake curve. Only when Snake is initialized near the target boundary will it converge to the desired boundary. 3) It can not get good convergence effect for the target contour of deep depression. 4) Due to the smoothness limitation, when the topology of the curve changes, like a curve is split into two, additional restrictions must be added, otherwise the curve will maintain the same topology (continuous smooth) as the original curve. 5) Because only the edge information of the image is used, the traditional Snake model has the same characteristics as the edge detection operator, such as missing detection or producing false edge.

Based on the segmentation algorithm of Snake model principle mentioned before, we segment the following 4 types of images (including 3 focus images).

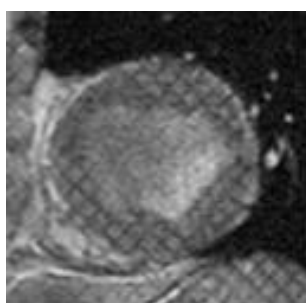


Figure 1. Primitive cell image

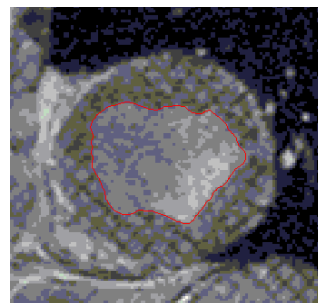


Figure 2. Image segmented by Snake model algorithm

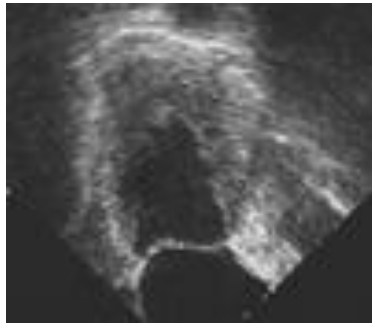


Figure 3. Original ultrasound image

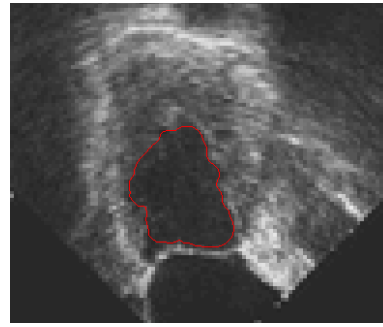


Figure 4. Image segmented by Snake model algorithm

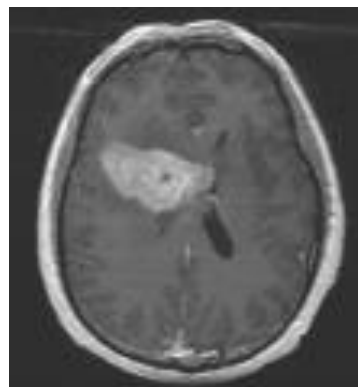


Figure 5. Original MRI image

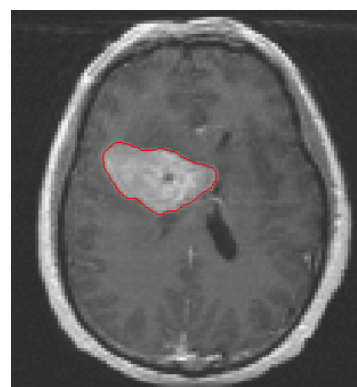


Figure 6. Image segmented by Snake model algorithm

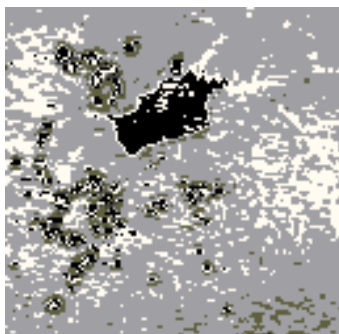


Figure 7. Image of primary intestinal lesions

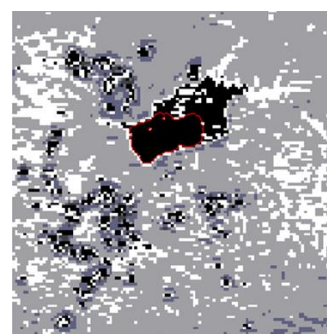


Figure 8. Image segmented by Snake model algorithm

According to the Snake model algorithm to segment different images, through the results, we can find that for the fuzzy image, the Snake model algorithm extraction effect is better and more accurate, but there are also shortcomings. Because of the large amount of calculation and the long time of calculation, the time of cell segmentation is 22.062783sec, ultrasonic segmentation is 7.314249sec, MRI is 6.217630sec, gastrointestinal focus segmentation is 14.358731sec. Moreover, it can be seen from the results that the segmentation effect of gastrointestinal lesions is not very ideal. The upper right focus area is not segmented, the effect is still not very accurate, and the detailed information of the contour is lost.

4.2. Image Recognition and Segmentation of Multiple Lesions Based on Discrete Dynamic Contour Algorithm

The following images are segmented with discrete dynamic contour algorithm for the following 4 types of images (including 3 focus images). First, input the image, initialize the segmentation

template, after many iterations, segmentation and marking effect, finally, it can also be converted into binary image, and complete the experiment in MATLAB environment.

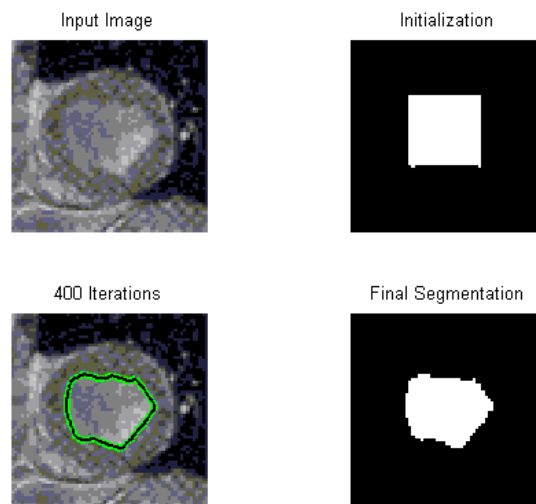


Figure 9. Cell segmentation markers based on discrete dynamic contour algorithm

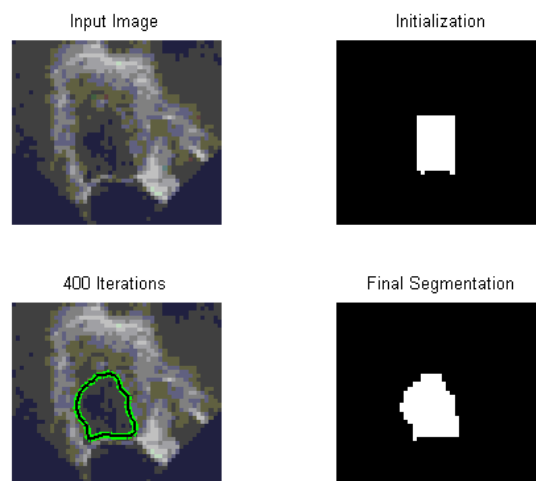


Figure 10. Ultrasonic image segmentation based on discrete dynamic contour algorithm

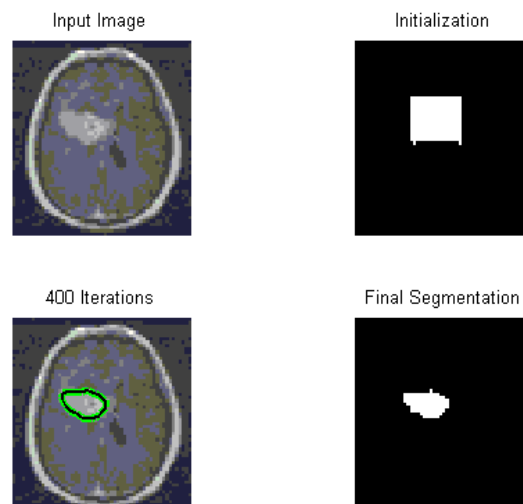


Figure 11. Segmentation and labeling of MRI based on discrete dynamic contour algorithm

According to the figure below, it is the segmentation and marking results after iterating for different times by using different initialization templates. It can be seen that a smaller number of iterations can be selected without affecting the segmentation effect.

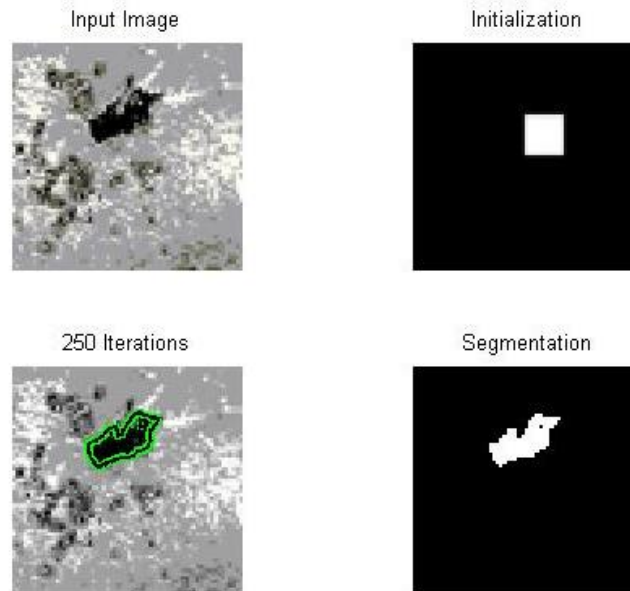


Figure 12. Segmentation of intestinal lesions based on discrete dynamic contour algorithm 1

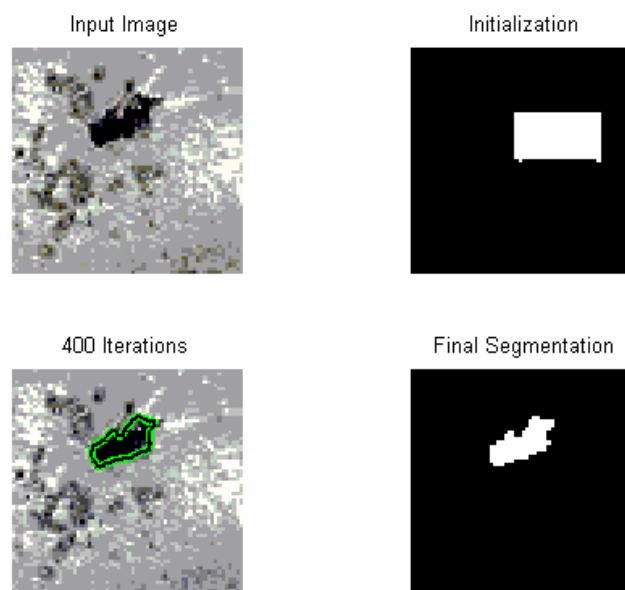


Figure 13. Segmentation of intestinal lesions based on discrete dynamic contour algorithm 2

The three parts of the total force have weighting coefficients, and according to the requirements, $0 < w^{im} \leq 1$, $0 < w^{in} \leq 1$, $-1 < w^d < 0$. After many tests, the following are selected: $w^{im} = 1.0$, $w^{in} = 0.3$, $w^d = -0.5$, $f_i^{tot}(t) = w^{im} f_i^{im}(t) + w^{in} f_i^{in}(t) + w^d f_i^d(t)$. In the calculation of the energy gradient value model of the image, the Gaussian smoothing $G_\sigma * I(x_i, y_i)$ uses the 2-D Gaussian filter, and the variance σ selects the 2.

Table 1. Experimental data based on discrete dynamic contour algorithm

	width	Height	Initialization	Iterations
cell	128	125	37:83,39:87	400
ultrasound	100	87	37:63,39:57	400
MRI	109	119	35:63,35:67	400
Intestinal lesions	128	125	55:87,65:97	250
Intestinal lesions	128	125	55:87,65:113	400

In Table 1, the data records of multiple experiments are included. According to Table 1, it can be known that different images have different heights and widths, different sizes, and different locations of target areas, so the design of the initialization template needs to be combined with human experience. Moreover, without affecting the segmentation effect, fewer iterations and smaller templates could be chosen.

In summary, it can be seen that the segmentation algorithm of the Snake model and the segmentation algorithm based on discrete dynamic contours are better than the traditional classic segmentation algorithms in terms of segmentation accuracy or segmentation accuracy. Among them, the segmentation algorithm based on discrete dynamic contour is more accurate than Snake model. But they also have their own limitations, such as their general processing speed is slow, algorithm calculation is large, but this problem can be realized by hardware acceleration (such as GPU) when the hardware is implemented.

5. Conclusion

In this study, Snake model based on parametric active contour model and discrete dynamic contour algorithm are used to recognize, segment and mark the focus tissue in the digestive tract. At the same time, the effectiveness, advantages and limitations of the two algorithms are verified by comparative experiments. From the aspect of computational efficiency, we can continue to improve the existing algorithm to speed up the evolution, and integrate other image information and prior knowledge (such as texture information, shape information, transform domain information, etc.), especially add shape prior knowledge, because when the target is occluded or the background is complex, it is difficult for the active contour model to only use the image features to get the correct score Cut the result. Therefore, how to extend the shape information of the object to the active contour model to improve the performance of image segmentation in complex background is a valuable research topic.

References

- [1] Cui Ming, Zhou Changxiong, Hu Zhifeng, Zhang Pei, Xu Rongqing. Image segmentation based on parametric active contour model of class variance [J]. Microelectronics and computer. 2010 (04): 145-148
- [2] Rafael C. Gonzalez, Richard E. woods, translated by Ruan Qiuqi et al. Digital image processing (Second Edition) [M]. Beijing: Electronic Industry Press, 2009
- [3] Zhu GuoPu. Image segmentation based on active contour model [D]. Harbin: Harbin University of technology, 2007.