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An Algorithm for Segmentation of Medical Image Series Based on Active Contour Model*

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Abstract: In this paper, an algorithm based on the combination of the live wire algorithm and the active contour model is proposed for the semiautomatic segmentation of medical image series. The traditional live wire algorithm is modified by integrating with the fuzzy region growing method. Then the improved live wire algorithm is applied to obtain accurate segmentation of one or more slices in a medical image series. Next, the computer will segment the nearby slice automatically using the active contour model. To record the local region characters of the desired object in the segmented slice, a gray-scale model is introduced to the boundary points of the active contour model. Based on the similarity measure of regions in the gray-scale model, a new energy function is defined to replace the external energy of the traditional active contour model. Finally, a simple method based on the idea of the live wire algorithm is introduced for the reparation of the automatic segmentation result to guarantee the reliability of the result. Experiment shows that this algorithm can obtain the boundary of the desired object from a series of medical images quickly and reliably with only little user intervention. It has practical value in the medical image analysis.

Key words: medical image processing; image segmentation; active contour; live wire algorithm; gray-scale model

Image segmentation plays an essential role in medical image processing. Accurate extraction of clinical information from medical images promises reliability for clinical applications and it is the basis of 3-D model reconstruction. Image segmentation is a very difficult problem in practice. Currently, fully automatic techniques for medical image segmentation are not likely to be able to match the requirement of practice for their unreliable performance, although the classic segmentation approaches have demonstrated their capability in various applications. In the recent years, a number of papers related to semiautomatic medical image segmentation techniques have been published[1], including live wire algorithm[2] and active contour models[3~11].

In practice, in order to obtain the boundary of a 3-D object, there's usually tens, even hundreds of slices to be segmented. Thus the convenience of the semiautomatic segmentation algorithms not only to segment a single slice, but also to segment a slice series, is very important for the practical application of the segmentation algorithm. In this paper, we proposed an algorithm for the semiautomatic segmentation of medical image series based on the

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combination of the live wire algorithm and the active contour model. In our segmentation algorithm, firstly we get accurate segmentation of one or more slices in a medical slice series by the live wire algorithm. Then the computer will segment the nearby slice using the active contour model. After the user amended the automatic segmentation result by some simple operation based on the idea of the live wire algorithm, the slices can be segmented one by one. Our algorithm modified the traditional live wire algorithm by combining it with the region growing method. In addition, we introduced a gray-scale model to the boundary points of the active contour model and replaced the external energy of the traditional active contour model with the energy decided by the gray-scale model.

Section 1 introduces the improved live wire algorithm. Section 2 describes the modified active contour model. Section 3 introduces our method for the amendment of the automatic segment results. Experimental results are given in Section 4 and we conclude in Section 5.

1 Improved Live Wire Algorithm

Interested reader can refer to Ref.[2] for detailed introduction of the live wire algorithm. The user has good control during the live wire segmentation process, thus the segmentation result of the live wire algorithm is reliable in practice.

The basic idea of the live wire algorithm is as follows: The image is considered as a graph, with the pixels as the nodes and the boundary of nearby pixels as the sides connecting nodes. After defining some cost function on the sides, we can trace the boundary of the desired object by graph searching. This boundary is the shortest path between two boundary points appointed by the user. Dynamic programming can be applied to find the shortest path.

Steps of the traditional live wire method is as follows:

Step 1. Compute the cost of all the sides in the graph.

Step 2. The user decides a point in the boundary of the desired object and the computer will compute the shortest path from this node to all the other nodes in the graph.

Step 3. As the user moves mouse, the computer will draw the shortest path from the previous user decided node to the current mouse position in the image. If the current mouse position is in the boundary of the desired object, the shortest path between the previous user-decided node and the current mouse position will be part of the boundary of the desired object.

Step 4. Repeat Step 2 and Step 3 until the boundary of the desired object is found.

There are two shortcomings in the traditional live wire method. Firstly, The dynamic programming module finds the shortest path from the appointed node to all the other nodes without any distinction, which makes it very slow. Secondly, the segmentation result relies too much on the cost function and parameters, and training is necessary before any segmentation, which makes the operation very complex and baffles its practical application.

In order to overcome these shortcomings, we combine the live wire method with some region growing method. In practice, before the live wire method is used, we apply the region growing method to obtain an over-segmentation of the image. During the live wire process, when the dynamic programming module is called, it is limited on the boundary of the regions decided by the over-segmentation. For this purpose, we need only remove the sides that are inside a region from the graph before applying dynamic programming to find the shortest path.

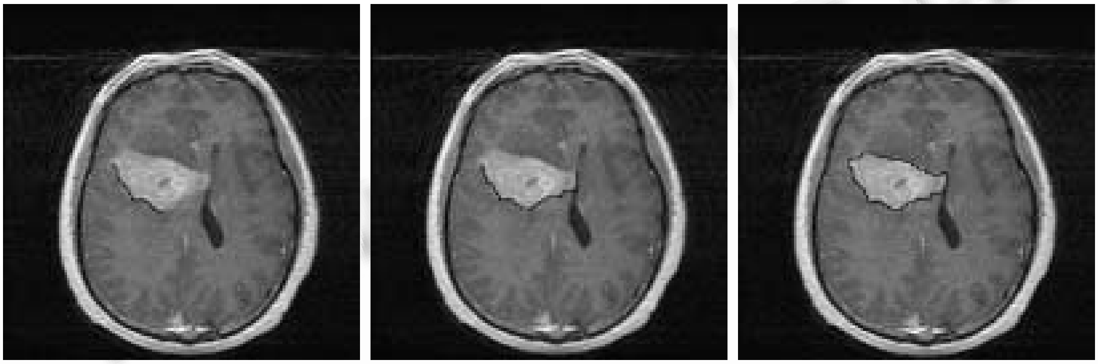
In practice, we can choose the region growing method according to the character of the image. In our experiment, the region growing method based on fuzzy connectedness[12] is used.

The merit of the combination of region growing method lies in three aspects. Firstly, the searching scope is limited and speed is much faster in dynamic programming. In our experiment, the time used in dynamic programming limited by over-segmentation is less than one quarter of that used without over-segmentation. Secondly, since the shortest paths are bounded to be potential boundaries of objects, the segmentation accuracy can be improved and the number of manual interventions would be decreased. Finally, the reliance of the segmentation result on the cost function and parameters is greatly decreased and training is no longer needed. The comparison between the improved live wire and the traditional live wire is shown in Table 1.

Table 1 Runtime comparison between two live wire algorithms

Algorithm	Image resolution (bit)	Number of interventions	Computing time (sec.)
Traditional live wire	256×256×16	6	12
Improved live wire	256×256×16	3	2

Figure 1 gives an example of the segmentation of one slice by the live wire algorithm. Figure 1(a) shows the starting boundary curve, (b) is the boundary curve in progress, (c) gives the final boundary of the desired object.



(a) (b) (c)

Fig.1 Segmentation of the head tumor by the live wire algorithm

2 Modified Active Contour Model

2.1 Traditional active contour model

Active contour model (or snakes), was first introduced by Kass *et al.*[3], and developed quickly in many directions[4~8]. It has proved very successful for medical image segmentation[9~11]. Active contours are curves defined within an image domain, that can move under the influence of internal forces within the curve itself and external forces derived from the image data. The internal and external forces are defined so that the snake will conform to an object boundary or other desired features within an image.

A traditional snake is a curve $v(s)=[x(s),y(s)]$, $s\in[0,1]$, that moves through the spatial domain of an image to minimize the energy functional

$$E(v(s))=E_{\text{int}}(v(s))+E_{ext}(v(s)) \tag{1}$$

where E_{int} is the internal deformation energy that characterizes the contour.

$$E_{\text{int}}(v(s))=\int_0^1(\alpha|v'(s)|^2+\beta|v''(s)|^2)\mathrm{d}s \tag{2}$$

where α and β are weighting parameters that control the snake's tension and rigidity, respectively, and $v'(s)$ and $v''(s)$ denote the first and second derivatives of $v(s)$ with respect to s.

The external energy function E_{ext} is derived from the image so that it takes on its smaller values at the features of interest, such as boundaries.

$$E_{ext}=\int_0^1 P(v(s))\mathrm{d}s \tag{3}$$

where $P(x,y)$ denotes a scalar potential function defined in the image plane. Examples of typical potential functions are $\pm G_\delta(x, y)*I(x,y)$ for lines and $-\left|\nabla(G_\delta(x,y)*I(x,y))\right|^2$ for step edges[3,10], where $I(x,y)$ is a gray-level image, $G_\delta(x, y)$ is a two-dimensional Gaussian function with standard deviation δ, and ∇ is the gradient operator.

According to the calculus of variations, the contour $v(s)$ which minimize the energy $E(v(s))$ must satisfy the Euler-Lagrange equation

$$\alpha v''(s) - \beta v''''(s) - \nabla P(v(s)) = 0. \tag{4}$$

To find a solution to equation (4), the snake is made dynamic by treating v as function of time t as well as s, i.e., $v(s,t)$. Then, the partial derivative of v with respect to t is set equal to the left-hand side of equation (4) as follows:

$$v_t(s,t) = \alpha v''(s,t) - \beta v''''(s,t) - \nabla P(v(s)). \tag{5}$$

When the solution $v(s,t)$ stabilizes, the term $v_t(s,t)$ vanishes and we achieve a solution of Eq.(4).

2.2 Modified active contour model

In the general application of active contour models in medical image segmentation[9,10], the boundary of the desired object in the segmented slice only provides the initial contour for the next un-segmented slice. Once the contour in the un-segmented slice is initialized, it will evolve based on the information of the un-segmented slice itself, without any relation to the slice that is already segmented. But in medical image series, the region statistics generally change slowly from one slice to the next, which means the statistics of the regions inside and outside the boundary of the desired object in the segmented slice are a good estimate of the statistics of the corresponding regions in the un-segmented slice. The information of the desired object in the segmented slice can not only provide the initial contour for the next un-segmented slice, but also help guide the contour in the un-segmented slice to evolve to the desired boundary.

In order to make full use of the statistic information of the regions inside and outside the boundary of the desired object in the segmented slice during the evolution of contour in the un-segmented slice, we will replace the potential function $P(x,y)$ of the external energy in Eq.(3) with a regional similarity measure.

In general, the active contour $v(s)(s\in[0,1])$ is represented by a set of contour points sampled along the contour. See Fig.2.

$$V=\{r_1(s_1),r_2(s_2),r_3(s_3),\ldots\} \quad 0\le s_1<s_2<\ldots\le 1 \quad r_i(s_i)=(x(s_i),y(s_i)).$$

In their active shape model, T.F. Cootes *et al.*[13] give a gray-scale model for each model point through training in order to fit the model to the image data. We will adopt their idea and attach a region based gray-scale model to each contour point in our active contour model. A similarity measure can then be defined on the gray-scale model to evolve the contour. Our gray-scale models are not learned from the training set, but adopted from the segmented slice.

To obtain the gray-scale model $GM(r_i)$ attached to a contour point r_i, we set a window centered on this contour point and record the region character of the regions inside and outside the desired object within this window. See Fig.2.

$$GM(r_i)=\{RF\_In(r_i), RF\_Out(r_i)\}$$

where $RF\_In(r_i)$ and $RF\_Out(r_i)$ are region characters of the inside and outside region respectively, in contour point r_i. The region character RF is represented by a set of features of the region.

$$RF = \{F_1, F_2, \ldots, F_n\}$$

where n is the number of features in the set, F_1 is the mean gray value of the region and F_2 is the variance of the region. The number of features used can be decided according to the character of the image. For example, if some objects in the image have apparent textures, texture features can be included in the feature set of the region. In our experiment, only F_1 and F_2 are used.

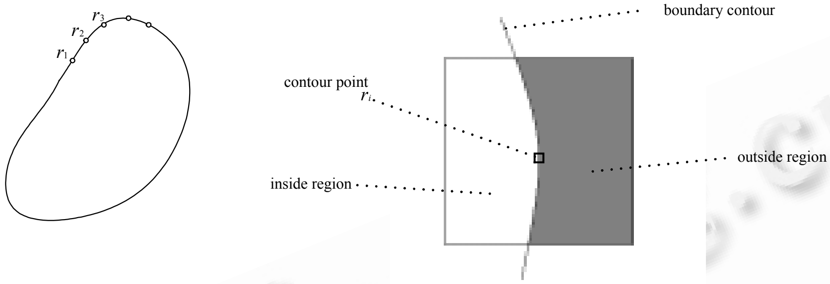


Fig.2 Active contour and regions near a contour point

After one slice is correctly segmented, the boundary of the desired object in that slice can be used as the initial contour for the next un-segmented slice. At the same time, we attach a gray scale model $GM(r_i)$ to each contour point r_i to record the characters of the local region inside and outside the desired object in the segmented slice. When the contour evolves in the un-segmented slice, we can obtain a similar gray scale model $gm(r_i)=\{rf\_In(r_i), rf\_Out(r_i)\}$ which is computed according to the image data in point r_i. We define $P(r_i)$ in Eq.(3) as

$$P(r_i) = -(S_{in}(r_i) + S_{out}(r_i) - S_{diff}(r_i)) \qquad r_i = (x(s_i), y(s_i)), \tag{6}$$

$$S_{in}(r_i) = \sum_{k=1}^{n} exp(-\frac{(F\_in_k - f\_in_k)^2}{\delta_k}) \quad F\_in_k \in RF\_In(r_i), f\_in_k \in rf\_In(r_i), \tag{7}$$

$$S_{out}(r_i) = \sum_{k=1}^{n} exp(-\frac{(F\_out_k - f\_out_k)^2}{\delta_k}) \quad F\_out_k \in RF\_Out(r_i), f\_out_k \in rf\_Out(r_i), \tag{8}$$

$$S_{diff}(r_i) = \sum_{k=1}^{n} exp(-\frac{(f\_in_k - f\_out_k)^2}{\delta_k}) \quad f\_in_k \in rf\_In(r_i), f\_out_k \in rf\_Out(r_i), \tag{9}$$

where $S_{in}(r_i)$ is the similarity measure of the inside regions of the segmented slice and un-segmented slice in contour point r_i. $S_{out}(r_i)$ is the similarity measure of the outside regions of the segmented slice and un-segmented slice in contour point r_i. $S_{diff}(r_i)$ is the similarity measure of the inside and outside regions of the un-segmented slice in contour point r_i.

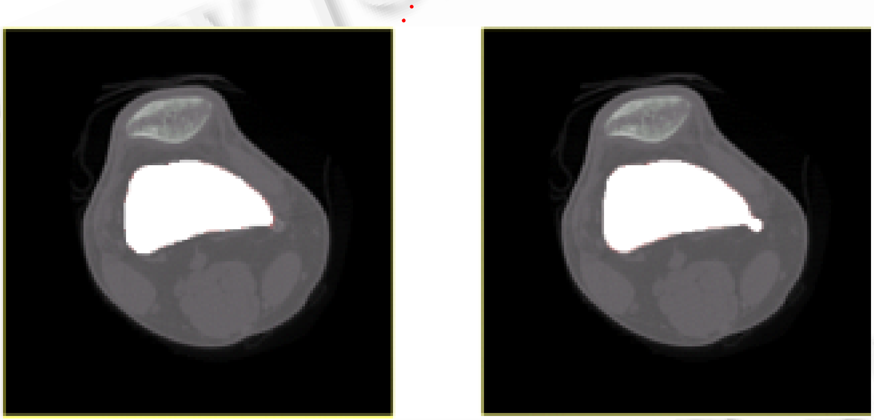
The information of the desired object in the segmented slice embodied in the gray scale model can help the contour to evolve to the desired boundary quickly and accurately in the un-segmented slice.

3 Amendment of the Segment Result

In the active contour model, after the contour is initialized, the evolution of the contour and the final result is out of the control of the user. Thus user intervention is necessary to guarantee the reliability of the segmentation result obtained by the active contour model.

In practice, we find that in general, only some local parts of the obtained boundary will deviate from the real boundary of the desired object. In addition, the deviated parts of the boundary are always in places where region statistics change comparably large from the segmented slice to the un-segmented slice and where object boundaries are not clear. Based on this observation, we propose to repair the automatic segmentation result by some simple operation based on the idea of the live wire algorithm. See figure 3. If part of the object boundary obtained by the active contour model deviates from the boundary of the desired object, the user select a point in the correct boundary and the computer computes the shortest path starts from this node, just as what was done in the live wire algorithm. The found path will stop once it reaches one of the points in the obtained boundary. By this operation, we will have a path between two points in the obtained boundary and we finish the reparation by replacing the part of the obtained boundary between these two points with the shortest path that passed the user selected point in the correct boundary. Figure 3 gives an example for the reparation of the segment result. Figure 3(a) shows the initial segment result, part of which is away from the true boundary of the desired object, and the point selected by the user in the true boundary. Figure 3(b) is the computer amended segment result. It can be seen that the amended segment result reflects the true boundary of the desired object.

User selected boundary point



(a) Initial segment result and user selected boundary point

(b) Amended segment result

Fig.3

The overall steps to segment a medical image series is as follows:

Step 1. Obtain an over-segmentation of all slices by region growing method.

Step 2. Using the live wire method to obtain the correct segmentation of one or more slices.

Step 3. Automatically segment the nearby un-segmented slice of the segmented slice by the modified active contour model. During the evolution of the contour, contour points are restricted to the boundary of regions obtained by over-segmentation.

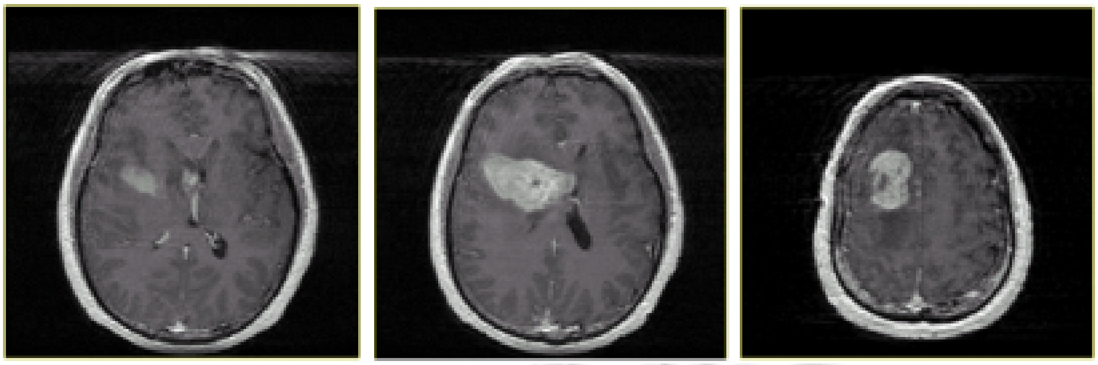
Step 4. Repair the automatic segmentation result to get correct boundary of the desired object.

Repeat Step 3 and Step 4 until all slices are segmented.

4 Experimental Results

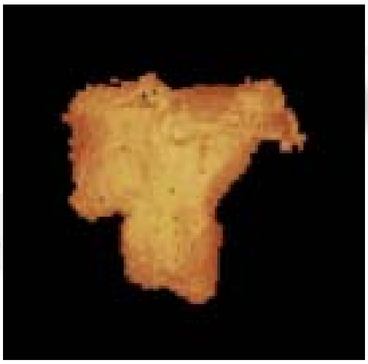
We have experimented our algorithm in the 3DMED medical image processing system developed by ourselves. The segmentation results of two of the image series are shown in Figs.4 and 5.

In medical image series, there are slices where object boundary are not clear, where region statistics change largely in some parts of the boundary between nearby slices and where even topology of the desired object changed between nearby slices. Our algorithm can handle all these situations and segment a series of medical images quickly and reliably with only little or no user intervention in each slice.



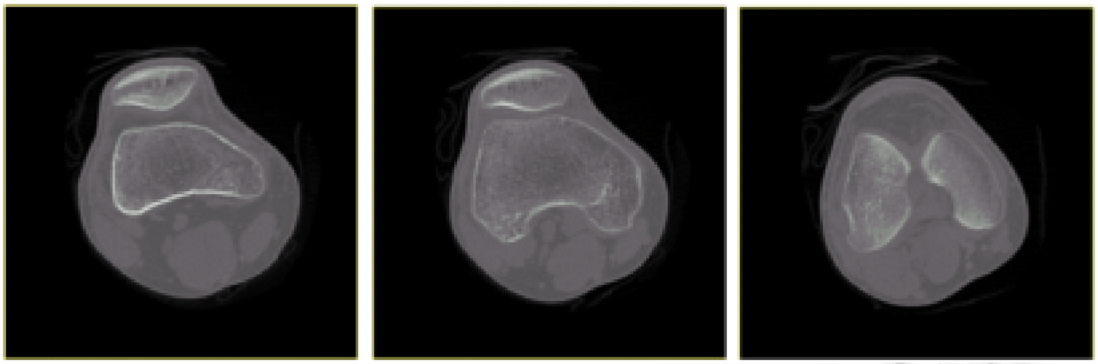
(a) Some slices in a medical series with a head tumor

(b) Segmentation result of the slices in (a)



(c) 3D display of the head tumor

Fig.4



(a) Some slices in a medical series of knee joint

(b) Segmentation result of the slices in (a)

(c) 3D display of the knee joint

Fig.5

5 Conclusions

In this paper, we discussed an algorithm for the semiautomatic segmentation of medical image series based on the combination of the live wire algorithm and the active contour model. We get accurate segmentation of one or more slices in a medical slice series by the live wire algorithm, and then the computer segment the nearby slice using the active contour model. User intervention is added after the automatic segmentation to guarantee the reliability of the result. We modified the traditional live wire algorithm by combining it with the region growing method. In addition, we introduced a gray-scale model to the boundary points of the active contour model to record the local region characters of the desired object in the segmented slice and replace the external energy of the traditional active contour model with the energy decided by the gray-scale model. Our algorithm can segment a series of medical images quickly and reliably with only little or no user intervention in each slice. Future research will focused on the further improvement of the active contour model to improve the reliability of the automatic segmentation step and reduce the requirement for user intervention.

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一种基于主动轮廓模型的医学图像序列分割算法

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摘要: 介绍了一种结合 live wire 算法和活动轮廓模型的医学图像序列的分割方法.通过把 live wire 算法和图像分割中一般的区域增长方法结合,对传统 live wire 算法进行了改进,并用改进后的算法对医学图像序列中的单张或多张切片进行交互式地准确分割.然后计算机利用活动轮廓模型自动分割相邻的未分割切片.还通过在活动轮廓模型的边缘点中引入记录已分割物体边缘附近局部区域特征的灰度模型,把已分割切片中的物体与背景的局部区域特征带入相邻的未分割切片中,并用由灰度模型定义的区域相似性代替活动轮廓模型中的外能来引导边缘轮廓收敛到物体的实际边缘.最后介绍了一种基于 live wire 算法思想的简单的分割结果交互式修复方法.实验结果表明该算法仅需少量用户交互就能快速准确地从医学图像序列中分割出感兴趣的物体,在医学图像分析中具有实用价值.

关键词: 医学图像处理;图像分割;主动轮廓;live wire 算法;灰度模型
中图法分类号: TP391 文献标识码: A