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Cardiac MR image segmentation using CHNN and level set method*

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Abstract: Although cardiac magnetic resonance imaging (MRI) can provide high spatial resolution image, the area gray level inhomogenization, weak boundary and artifact often can be found in MR images. So, the MR images segmentation using the gradient-based methods is poor in quality and efficiency. An algorithm, based on the competitive hopfield neural network (CHNN) and the curve propagation, is proposed for cardiac MR images segmentation in this paper. The algorithm is composed of two phases. In first phase, a CHNN is used to classify the image objects, and to make gray level homogenization and to recognize weak boundaries in objects. In second phase, based on the classified results, the level set velocity function is created and the object boundaries are extracted with the curve propagation algorithm of the narrow band-based level set. The test results are promising and encouraging.

Key words: cardiac MR image, image segmentation, curve propagation, level set, narrow band, competitive hopfield neural network.

1. INTRODUCTION

At present, magnetic resonance imaging (MRI) technology is widely used in the disease diagnosis for human organic and tissue (such as cardiovascular, brain). However, due to the imaging mechanism and the complexities of the construction of the organic and tissues, the phenomenon of the area gray level inhomogenization, the weak boundaries and the artifact often can be found in MR images. These shortages lead to the difficulty of the MR images segmentation with the gradient-based algorithm. As shown in Fig. 1 'cardiac MR image', due to the blood flow and the gray level inhomogenization at the endocardiac boundary, an artifact and a weak boundary can be found in left ventricle area. In Fig. 2 'shrinking cardiac MR image of the left ventricle', due to gray level inhomogenization inside the left ventricle, a local maximum of gradient is obtained. As usually, the edge-based image segmentation methods depend on the information of maximum gradient. Thus, the conventional gradient-based algorithm is not promising in the segmentation of the medical images. As shown in Fig. 3 'the segmentation result of Fig. 2 with Canny operator', the breakpoints and the wrong segment energe on the endocardiac boundary.

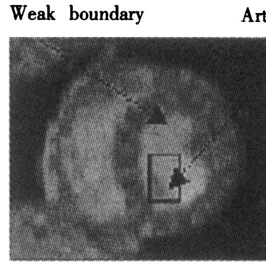

Fig. 1 Cardiac MRI

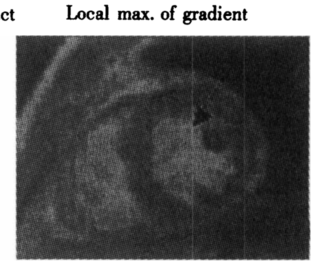

Fig. 2 Cardiac MRI

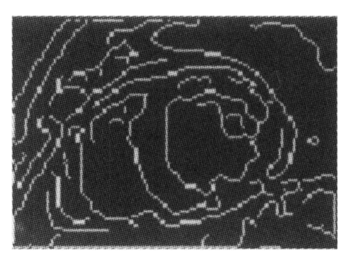

Fig. 3 Segmentation result of Fig. 2 with Canny operator

Due to the task of the medical images segmentation is only limited in region of interest, the algorithms based on the deformed models have been lucubrated and widely used in medical images segmentation in recent. The parameter active contour model[1]

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can automatically deform to match real edge on the image through minimizing an energy function. But there are two key difficulties with it. First, the initial contour must, in general, be close to the true boundary or else it will likely converge to the wrong result. The second problem is that active contours have difficulties to progress into concave boundary region. In order to solve the problem of the region's gray level inhomogeneity and the weak boundary, researchers have proposed a lot of solutions, such as the statistic method, based on prior knowledge[2], the method based on gray level comparability[3], and the WaterShed algorithm[4]. In general, these methods often combin the information of the gradient and the region.

In this paper, we propose an algorithm for the cardiac MR image segmentation. The algorithm consists of two stages: first, to get the homogeneity object regions, a competitive hopfield neural network (CHNN) is adopted to classify the image objects. Then, the curve propagation algorithm[5], based on the narrow band level set, is adopted to extract the boundary of the objects. The segmentation results of the algorithm are encouraging and promising.

In Section 2, we briefly introduce the CHNN clustering algorithm and its application to the MR image object classification. In Section 3, we introduce the algorithm of the curve propagation based on narrow band level set. In Section 4, we define the velocity function of the level set. In Section 5, the tests of the cardiac MR image segmentation are carried to validate the efficiency of our algorithm and in Section 6 some conclusions are given.

2. CHNN CLUSTERING ALGORITHM AND THE CLASSIFICATION OF IMAGE OBJECTS

Given an image having L gray levels, N pixel points and C objects, then, $N = \sum_{x=0}^{L-1} n_x$, $h_x = n_x/N$. Here n_x is the number of the pixel with x gray level, h_x is gray level histogram. Suppose g_x and g_x express the two objects with the mean gray level x and y respectively. The distance between the two objects is defined as $d_{x,y} = (g_x - g_y)^2$. For all appearances, $d_{x,y} = d_{y,x}$. The CHNN used in the segmentation of image defined above consists of $L \times C$ 2-D neural cells matrix[6]. At stabilization, the following relations are satisfied

$$V_{x,i} \in \{0,1\},\ \sum_{i=0}^{C-1} V_{x,i} = 1, 0 < \sum_{x=0}^{L-1} V_{x,i} < L$$
$$\sum_{x=0}^{L-1}\sum_{i=0}^{C-1} V_{x,i} = L \tag{1}$$

Where i notifies the category, $V_{x,i}$ the neural status at the (x,i) in the 2-D matrix.

The energy function is as follows

$$E = \frac{A}{2}\sum_{x=0}^{L-1}\sum_{y=0}^{L-1}\sum_{i=0}^{C-1} \frac{1}{\sum_{y=0}^{L-1} h_y V_{y,i}} V_{x,i} d_{x,y} h_y V_{y,i} + \frac{B}{2}\sum_{x=0}^{L-1}\sum_{i=0}^{C-1}\sum_{\substack{j=0\\ j\neq i}}^{C-1} V_{x,i}V_{x,j} + \frac{C}{2}\Big[\Big(\sum_{x=0}^{L-1}\sum_{i=0}^{C-1} V_{x,i}\Big) - L\Big]^2 \tag{2}$$

where A, B, C are the weighted coefficients, the first item is the mean distance between each gray level and other one in same category, the second and the third items satisfy the formula (1). By the winner-takes-all (WTA) learning algorithm, the winner neural cell has the max. input outputs 1, the other outputs 0. That is, for the x gray level, the following relation is satisfied

$$V_{x,i} = \begin{cases} 1, & \text{if } \mathrm{Net}_{x,i} = \max\{\mathrm{Net}_{x,0}, \mathrm{Net}_{x,1}, \cdots, Net_{x,C-1}\} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where $i = 0, 1, \cdots, C-1$. Thus, formula (1) can be simplified to

$$E = \frac{1}{2}\sum_{x=0}^{L-1}\sum_{y=0}^{L-1}\sum_{i=0}^{C-1} \frac{1}{\sum_{y=0}^{L-1} h_y V_{y,i}} V_{x,i} d_{x,y} h_y V_{y,i} \tag{4}$$

From formula(4), the total input of the neural cell at (x,i) can be deducted as follows[6]

$$\mathrm{Net}_{x,i} = \frac{-1}{\sum_{y=0}^{L-1} h_y V_{y,i}} \sum_{y=0}^{L-1} d_{x,y} h_y V_{y,i} \tag{5}$$

Algorithm 1: the classifying-based CHNN algorithm for cardiac MR images

(1) Smoothing image and noise removal;

(2) Giving C and L to construct the $L \times C$ 2-D CHNN matrix;

(3) According to condition formula (1), initializing the status of all neural cells;

(4) By formulas (5) and (3), updating each cell status repeatedly until outputs of all cells are not changed;

(5) Outputting results. Ending classification.

Using Algorithm 1, we can solve the problem of gray level inhomogeneity in same region and of weak boundary. For example, for Figs. 1 and 2, given C and L are 3 and 256 respectively, the classifying results are showed in Figs. 4 and 5, where the pixels of the left ventricle having gray level inhomogeneity are classified to the same category, the weak boundary in Fig. 1 also is well managed, the region having local max. gradient in Fig. 2 is removed.

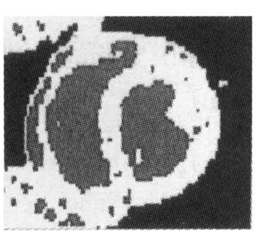


Fig. 4 The classification of Fig. 1

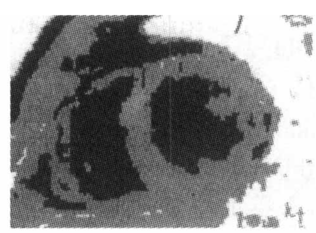


Fig. 5 The classification of Fig. 2

3. CURVE PROPAGATION BASED ON NARROW BAND LEVEL SET

An closed curve $\gamma(0)$ in image field can be denoted latently to a zero level set of a spatial surface with the level set method: $\{\gamma(0) = (x, y) \mid \varphi(x, y) = 0;\}$. Thus, the motivation of the curve is changed to the deformation of the surface. In this way, in spite of the increased complexity of solving problem, many advantages appear. For example, it is able to naturally treat with the change of curve topology, to get lot of the geometry properties of curve, such as the curvature, normal vector, et al[7]. For the zero level set curve as the evolution of the surface, its motivation equation may be defined as follows

$$\phi_t + \frac{\partial \phi}{\partial x}\frac{dx}{dt} + \frac{\partial \phi}{\partial y}\frac{dy}{dt} = 0 \qquad (6)$$

Suppose the normal motivation velocity of the surface is F, then formula (6) can be deducted to formula (7), a partial differential equation (PDE) initial value problem

$$\phi_t + F|\nabla \phi| = 0$$
$$\phi(x, y, 0) = d(x, y) \qquad (7)$$

where $d(x, y)$, the signed distance function(SDF), denotes the shortest distance between the point (x, y) and $\gamma(0)$ and its sign depends on the position of the point: a minus(plus) is assigned to it if the point is situated inside the curve, contrariwise, a plus(minus) is assigned to it if the point is situated outside the curve. In general, F is relative to the image data and the geometry properties (such as curvature) of the level set curve. The level set equation mentioned above is belonged to the Hamilton-Jacobi one and its numerical solution can be found in Ref. [5]. Because the plane curve propagation be expanded to the 3-D surface deformation, and whole image plane is taken as the solution region, the calculation complexity is much enlarged in the method. In Ref. [8], the narrow band level set method was proposed: the numerical calculation is limited in a narrow band of the curve surrounding. When the curve is propagated to the edge of the narrow band, the new narrow band, centered in current curve, is created. But compared with the direct method, this method would produce the error in calculation of the shortest distance and infect the numerical calculation[9].

On account of the less narrow band width (about 9 pixels), a method of creating narrow band using distance function template is presented in this paper. Suppose the width of the narrow band is k, the $k * k$ distance function template is defined as follows (take $k = 3$ as example). The each value in the template indicates the Euclidean distance to the center point.

1.414	1	1.414
1	0	1
1.414	1	1.414

Given initial contour, the point at curve is taken as the center of the template to traverse all over the curve. The pixel point located in template is marked as the one in narrow band and its shortest distance from the curve, d, is taken as the template value. The point corresponding to the smallest d is chosen as the center point. If the pixel point falling in the template has been marked in the narrow band, then its d can be written: $d = \{$the corresponding point value at the template, the shortest recorded distance of the point to the curve}.

Algorithm 2: the zero level set curve propagation algorithm based on the narrow band

(1) Initializing zero level set curve, marking the points in region encircled by the curve, the ones at curve, and the ones outside the region;

(2) Creating narrow band using the distance template. Considering the mark of the point to gain SDF;

(3) Recognizing the boundary point. Take the point close to the boundary point as the checked point. During solving equation, if the sign of any checked point is changed, it can be considered that the zero level set curve is propagated to the boundary of the narrow band and it is necessary to reinitialize the narrow band;

(4) Extending the velocity item. The normal velocity of the surface propagation is relative to the curvature of the zero level set curve, but the curvature of the curve is only defined on the zero level set, so it is necessary to extend the normal velocity all over the narrow band. According to Step 2, the narrow band point's curvature is directly taken as the one of the corresponding point at curve;

(5) Fixing boundary condition. Solve the level set equation with the finite difference method. In order to stabilitze numerical scheme, the step size of the finite format should be necessarily chosen to satisfy the CFL condition. Suppose h is space step size and Δt is time step, the 'entropy-satisfying' finite format of the level set equation is[5]

$$\phi^{n+1} = \phi^n - \Delta t(\max(F_{x,y},0)\nabla^+ + \min(F_{x,y},0)\nabla^-) \tag{8}$$

where

$$\begin{aligned}
\nabla^+ &= \max(D_{i,j}^{-x}, 0)^2 + \min(D_{i,j}^{+x}, 0)^2 + \max(D_{i,j}^{-y}, 0)^2 + \min(D_{i,j}^{+y}, 0)^2 \\
\nabla^- &= \min(D_{i,j}^{-x}, 0)^2 + \max(D_{i,j}^{+x}, 0)^2 + \min(D_{i,j}^{-y}, 0)^2 + \max(D_{i,j}^{+y}, 0)^2 \\
D_{i,j}^{-x} &= \frac{\phi_{i,j} - \phi_{i-1,j}}{h},\ D_{i,j}^{+x} = \frac{\phi_{i+1,j} - \phi_{i,j}}{h} \\
D_{i,j}^{-y} &= \frac{\phi_{i,j} - \phi_{i,j-1}}{h},\ D_{i,j}^{+x} = \frac{\phi_{i,j+1} - \phi_{i,j}}{h}
\end{aligned} \tag{9}$$

In order to improve the numerical precision, we adopt the upwind difference scheme formula (8) for the space gradient and the 3-TVD-Runge-Kutta formula (9) for the time one[12];

(6) Calculating the zero level set curve when the curve is propagated to the narrow band boundary. Justifying either stopping calculation or reinitializing the narrow band to continue calculation.

4. VELOCITY FUNCTION OF LEVEL SET

In image segmentation, the zero level set curve propagation should be stopped when it arrives at the boundary. If there is the boundary leakage, it should have the ability to pull the curve back to the boundary. To do it, Paragios and Deriche added an attracting boundary term to the level set equation[10]

$$\frac{\partial \phi}{\partial t} = c(x)(V_0 + \varepsilon K) + \beta \nabla c \cdot \nabla \phi \tag{10}$$

where $c(x)$, namely stopping term, is related to the strength of the gradient and often is adopted as follows

$$c(x) = \frac{1}{1 + \| \nabla G_\sigma * I \|^n} \tag{11}$$

The 2nd term in formula (10) is the projection in normal direction the image data force of acting on the deforming surface. The β is a parameter to control the attracting strength. $\nabla c \cdot \nabla \phi$ can attract the curve front near the boundary to the image boundary. In fact, the problems of curve propagation stopped at the local maximum gradient and the boundary leakage can not be completely overcome by formula (10)[11]. An available method is to add the region information to the model to improve the segmentation effect.

In this paper, based on the result of the Algorithm 1, we define a velocity function for the object segmentation in ROI as follows

$$F = F_r(V_0 + \varepsilon K) + \beta(1 - F_r)\nabla c \cdot \nabla \phi / \| \nabla \phi \| \tag{12}$$

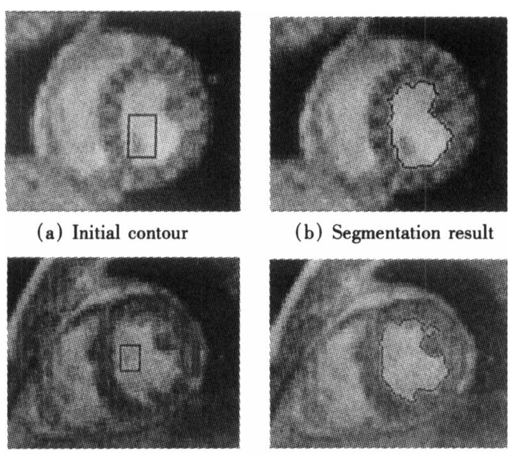
where

$$F_r = \begin{cases} 1, & \text{if } I_i \in C_i \\ 0, & \text{else} \end{cases}$$

In formula (12), when the curve is propagated from inside object to boundary, the 2nd term becomes 0 and the 1st term becomes $V_0 + \varepsilon K$ to push the curve to the boundary. Here, V_0 and εK approximately equal the balloon force and rigid force respectively. When arriving at boundary, the 1st term becomes 0, the 2nd term attracts the curve to real boundary.

5. CARDIAC MR IMAGE SEGMENTATION

Take the Figs. 1 and 2 as examples to validate our algorithm. First, we use the Algorithm 1 to classify the objects in MR images. Then, according to formula (12), we define the velocity function, the relative parameters are as follows: $V_0 = 1$, $\varepsilon = 0.2$, $\beta = -1$, and the number of iteration is 100. The initial contours and segmentation results are showed in Fig. 6.



(a) Initial contour (b) Segmentation result

(c) Initial contour (d) Segmentation result

Fig. 6 The segmentation results: (a) and (b) are corresponding to Fig. 1; (c) and (d) are corresponding to Fig. 2

Due to existing artifact in the region of the left ventricle, the initial contour is set outside the artifact region to let $F_r = 0$. The test results show that the curve propagation is not leaked out the weak boundary and not affected by the local maximum gradient.

6. CONCLUSIONS

In this paper, combining the CHNN clustering with the narrow band level set method, a MR image segmentation algorithm is presented. The CHNN clustering method can efficiently overcome the most common problems of the MR images, that is, the local maximum gradient, the weak boundary and the gray level inhomogeneity in the ROI. Because the region information is combined with the boundary gradient in the velocity function of the level set propagation and a fast method of creating narrow band using distance function template is presented, the algorithm can efficiently implement the MR images segmentation. The tests on the real cardiac MR images are promising and encouraging. It should be pointed out that the construction of the level set velocity much depends on the result of classification, it is important to improve the preciseness of the classification to finish more credible segmentation.

7. ACKNOWLEDGEMENT

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