Abstract – In this paper an approach to extract the Left Ventricle (LV) endocardium contour by proposing an improved Distribution Matching (DM) algorithm is presented, the main idea of which is to match the distribution of grayscale and distance constrained by gradient vector flow (GVF) force field between the sample and the images input. The endocardium contour is then regarded as the initial iterative curve of Active Contour Model (ACM) to obtain the epicardium contour with a method of local circular constraints and adaptive changing parameter of external force field. The approach has been applied on data of 20 subjects, and results have demonstrated simpler user interaction, more robustness and higher segmentation accuracy compared to LV segmentation methods published previously.

Keywords: distribution matching, image, contour model

1 Introduction

The technology of computer image processing and computer vision have been applied in different areas. In the real world, Heart Failure (HF) is one of the leading causes of death. According to statistics, there are 1200~1500 patients with HF all over the world, and up to 5% patients with HF among one billion of the population in European and American. Thus it’s significant to develop an automatic detection method for HF’s early diagnosis. Paulus et al. [1] and Doughty [2] detailed the importance of utilizing LV Ejection Fraction (LVEF) which can be obtained by Cardiac Magnetic Resonance Images (CMRI) segmentation, in HF’s diagnosis. However, although the automatic segmentation of CMRI has been intensively studied in computer vision, because most existing LV segmentation algorithms requires either intensive user inputs, extensive training sets, or with low accuracy and efficiency produced, it might limit its further application in the medical process. To overcome these problems, in this paper, an improved Distribution Matching (DM) algorithm and Active Contour Model (ACM) are proposed to be used to extract the LV endocardium and epicardium. The experiment results show that our method is more efficiently.

2 Related works

The segmentation algorithms of medical images can be categorized in terms of the mathematical model they used, such as clustering analysis method, statistical method, graph cut method, deformable model methods, cardiac model-based method, distribution matching method and etc.

Clustering analysis method is often applied to MRI segmentation with Gaussian Mixture model (GMM) and K-means. For instances, Lynch et al. [3] used grayscale feature and K-means to cluster, and extracted the myocardium area. Klann et al. [4] used K-means constrained by boundaries (edge features) for breast MRI segmentation. But cluster analysis method is easily influenced by uneven grayscale distribution and need special threshold configuration.

Statistical method mainly involves two kinds of random field, Markov Random Field (MRF) and Conditional Random Field (CRF), such as the image segmentation method proposed by Chittajallu et al. [5], who utilized MRF with shape prior, edge prior and label prior for Computed Tomography images segmentation. When working with graph cut method, it performs well but needs extra computation. Similarly, Grosgeorge et al. [6] proposed a method to calculate the summary of grayscale energy and classification tags energy by graph cut method to obtain the optimal segmentation. And Mahapatra et al. [7] detailed a method for CMRI segmentation by combining graph cut method and shape priors.

Deformable model method is used to solve image segmentation problems with partial differential equations, by modeling the CMRI with energy function by the internal energy and external energy for numerical solutions. For instance, Wang et al. [8] combined ACM and GMM to obtain the epicardium and endocardium contour of LV, Klann et al. [9] proposed a Mumford-Shah Level-Set approach for tomography’s reconstruction and segmentation, Lee et al. [10] detailed a method for CMRI segmentation by combining graph cut method and shape priors.

Cardiac model-based method is used to map a three dimensional cardiac model to a two dimensional CMRI by calculating the internal energy and external energy of the CMRI[12]. But it requires to generate a three dimensional CMRI model first, and the reflection also need extra computation although by using principal component analysis[11].

Distribution matching method is used to convert image segmentation problems to the functional optimization problems, by establishing energy functional equations and using Euler-Lagrange partial differential equation to solve the problems. Similarly, Njeh et al. [13] used two constraints to
solve the brain tumor segmentation problem, one is the intensity distribution prior, and another is the smoothness prior; and Nambakhsh [14] proposed a convex relaxed distribution matching (CRDM) method, which utilized three kinds of constraints to obtain the myocardium area: intensity, distance and edge. Distribution matching method can be performed well because it converges to a distribution which has the most similarity of the distribution calculated by the sample. But it needs extra computation and sometimes too easy to be influenced by the sample distribution, which make the converged curve lack its meaningful description.

In this paper, a CMRI segmentation method combining with DM method is proposed to reduce amount of dataset, which only needs one CMRI input, and ACM is reported to be used to obtain a smooth and accurate contour with higher accuracy and more robustness. The improved DM algorithm is based on the grayscale and gradient features of LV chamber constrained by the gradient vector flow (GVF) force field. The original iterative curve of ACM is then obtained by using the contour of endocardium. A local circular constraint and a method of adaptive changing parameter of external force field are also proposed to improve the ACM in LV epicardium extraction. After being performed on data of over 20 subjects, the proposed algorithm has been demonstrated its robustness and accuracy when uneven grayscale distribution and mastoid muscle prompted. Besides, the character of simple user interaction has great application in HF’s early diagnosis.

3 The improved left ventricular segmentation algorithm

There are two steps involved for the proposed LV segmentation method: 1) an image from base of heart with endocardium contour drawn from the CMRI sequence of a given subject is needed to be the sample to calculate the grayscale distribution, then match the distributions constrained by distances and GVF feature between sample picture and input picture every iteration to perform the endocardium contour extraction; 2) convert the results in step 1 as the initial iterative curve, and an improved ACM is used to obtain the epicardium contour.

3.1 Improved distribution matching

DM algorithm has been demonstrated its outstanding images segmentation results, such as in CRMI segmentation[14, 15] and in daily scene images segmentation[16]. Therefore, we propose a DM-based method to extract the chamber area.

Let $E_{\text{gray}}(k)$ be grayscale energy, $E_{\text{distance}}(k)$ be the distance energy, and $c_{\text{gv}}(k)$ be the edge energy of the input images. $E_{\text{gray}}(k)$ means the similarity of grayscale distribution between chamber area of the sample image, defined as $T_{\text{in}}(x)$, and the image input later, defined as $T_{\text{in}}(x)$. If these two distributions are similar enough, $E_{\text{gray}}(k)$ will be small enough. $E_{\text{distance}}(k)$ is defined as the energy to make sure that in every iteration, the iterative area is similar to a circle, or at least, it’s smooth enough. We define $E_{\text{distance}}(k)$ as the edge energy, which can be calculated by GVF [17]. Then we need to solve such energy functional optimization problem:

$$E_{R_c} = \min_{R_c} \mathcal{E} = \int_{R_c} E_{\text{gray}}(k) ds + \theta \int_{R_c} E_{\text{distance}}(k) ds + \lambda \int_{\partial R_c} c_{\text{gv}}(k) ds$$

(1)

where $\theta$, $\lambda$ and $\lambda$ are the weights of $E_{\text{gray}}$, $E_{\text{distance}}$ and $c_{\text{gv}}$. $R_c$ is the iterative area and $\partial R_c$ is its boundary.

![Fig.1. Grayscale distribution of chamber area in a series of input CMRI. The red line is the distribution of the sample images of the base and the blue lines are other flames of CMRI. It is clear that almost the chamber areas of all flames have the similar grayscale distribution.](image)

Let $P(R, Z)$ be the grayscale distribution (Figure 1 shows the CMRI sequence input from base to apex, counts for 7 images), $I(x)$ be the grayscale feature of the input images, and $u(x) \in (0, 1)$: when $u(x) = 1$, the iterative area belongs to chamber area ($R_c$), and when $u(x) = 0$, the area is out of chamber ($R_q$). $P(R, Z)$ is defined as follows:

$$P(R, Z) = \frac{\sum_{\mathcal{R}} K_n(I(x)) u(x)}{\sum_{\mathcal{R}} u(x)}$$

(2)

$K_n(x)$ is given by Gaussian Core function, where $n \in \{1, 2, 3, 4\}$, and when $n=4$, $K_4(x)$ is typical Gaussian Core function, defined as follows:

$$K_n(x) = \frac{1}{(2\sigma^2)^n} \exp \left( -\frac{\|x - z\|^2}{2\sigma^2} \right)$$

(3)

$R(P, M)$ is defined as the similarity between distribution $P$ of $T_{\text{in}}(x)$ and distribution $M$ of $T_{\text{sam}}(x)$ calculated by Kullback-Leibler divergence is defined as follows:

$$R(P, M) = \sum_{z=0}^{N} \ln \frac{P(z)}{M(R, Z)} P(z)$$

(4)

But only $E_{\text{gray}}(k)$ is unable to obtain the optimal edge of endocardium, so we add another constraint: $E_{\text{distance}}(k)$, which is the energy of the distance from the points $p$ of $R_c$ to $O(x)$, the center point of $T_{\text{sam}}(x)$, where we can get $O(x)$ defined as follows:

$$O(x) = \frac{\sum_{R_c} x u(x)}{\sum_{R_c} u(x)}, R_c \in T_{\text{sam}}(x)$$

(5)

So $E_{\text{distance}}(k)$ can be obtained as follows:
\[ E_{\text{distance}} (k) = \sum_{r \in R} \sqrt{\|p - O\|^2 - R^2} \]  

with \( \bar{R} \) as the mean radius of \( R_c \).

We calculate \( \varepsilon_{gv}(k) \) by GVF. Because the energy calculated by \( \Delta I(x) \) can be only obtained on the edge, which makes \( E_{\bar{R}_c} \) only be constrained by \( E_{\text{gray}} \) and \( E_{\text{distance}} \) when the iterative area excludes the edges or intensively constrained by the edge when the iterative area includes the edges. But GVF force field will lead the iterative area to the edges, which can converge to the optimal area. \( \varepsilon_{gv} \) and \( \varepsilon_{gv} \) are defined as follows:

\[ \varepsilon_{gv} = \sqrt{G(b,v)^2}, \quad \varepsilon_{gv} = \frac{1}{1 + \delta \varepsilon_{gv}} \]  

with \( G(b,v) \) defined as GVF force field [17]:

\[ \varepsilon_{gv} = \int \mu(\nabla^2 u) + |\nabla|^2 (G - \nabla I) \, dx \, dy \]  

To make \( \varepsilon_{gv} \) to 0, we get \( b \) and \( v \) as follows, where \( k \) is the iteration times.

\[
\begin{align*}
\{ b^{k+1} & = b^k + \mu \nabla^2 b - (g_x^2 + g_y^2)(b^k - g_x) \\
\{ v^{k+1} & = v^k + \mu \nabla^2 v - (g_x^2 + g_y^2)(v^k - g_x)
\end{align*}
\]  

Now \( E_{\text{gray}}(k) \), \( E_{\text{distance}}(k) \), and \( G_{uv}(k) \) are available to achieve, so when \( E_{\bar{R}_c} \rightarrow \min \), \( u(x) \) will converge to the optimal chamber area. Our algorithm of calculating area \( u(x) \) is something like area growing algorithm. We define an initial area \( u(x)^0 \) with the center of \( O(x) \) (e.g., a circle with radius of 5 px) and a dilation template \( B \) (e.g., 3x3 or 5x5). We perform \( B \) to \( u(x)^k \) to achieve \( u(x)^{k+1} \) and define \( \Delta u(x)^{k+1} = u(x)^{k+1} - u(x)^k \) as shown in Figure 2.

Let \( \Delta u \) be constrained by energy function \( E_{\bar{R}_c} \), so we convex \( u \in [0,1] \) to \( u(x) \in [0,1] \). Define \( p(x) \in I(x) \cdot \Delta u, \ x \in R \).

For any \( p(x) \), define \( E_{\text{gray}}(p) = R(\bar{P}_{\text{gray}}, \bar{M}_{\text{gray}}) \), where \( P \) is the distribution of \( p(x) \) and \( M \) is the distribution of sample \( T_{\text{sam}}(x) \). The edge function of \( p(x) \) is defined as following, where \( C_{u^{k+1}}(x) \) is the edge of \( u(x)^{k+1} \) calculated by Canny edge detector mentioned [18]:

\[ E_{\text{edge}}(p) = \sum_{x \in R} \frac{C_{u^{k+1}}(x)}{1 + \delta E_{\text{gv}}(x)} \]  

So \( \Delta u(x)^{k+1} \) can be updated as following:

\[ \Delta u(x)^{k+1} = \varphi R(\bar{P}_{\text{gray}}, \bar{M}_{\text{gray}})^* + \theta E_{\text{distance}}(p)^* + \lambda E_{\text{edge}}(p)^* \]  

\( R^* \) being normalized by \( R \), \( E_{\text{edge}}^* \) being normalized by \( E_{\text{edge}} \), \( E_{\text{distance}}^* \) being normalized by \( E_{\text{distance}} \), and \( \varphi + \theta + \lambda = 1 \). So \( \Delta u(x) \) can be constraint to \([0,1] \). To make \( u(x) \in [0,1] \rightarrow u(x) \in [0,1] \), we defined a constant \( \omega \) to binary-value area \( \Delta u(x)^{k+1} \), as follows:

\[ \Delta u(x)^{k+1} = \begin{cases} 1, & \text{when } \Delta u(x)^{k+1} \leq \omega \\ 0, & \text{when } \Delta u(x)^{k+1} > \omega \end{cases} \]  

and redefine \( u(x)^{k+1} = u(x)^{k^*} + \Delta u(x)^{k+1} \).

The global energy \( E^{k+1} \) is calculated as follows:

\[ E^{k+1} = \varphi R(\bar{P}_{\text{gray}}, \bar{M}_{\text{gray}})^* + \theta E_{\text{distance}}(p)^* + \lambda \sum_{x \in R} C_{u^{k+1}}(x) \]  

Because \( R \) decreases monotonically with distribution \( P \) being similar with distribution \( M \), \( E_{\text{distance}} \) also decreases monotonically with the area \( R_c \) being smooth, and edge energy decreases monotonically with edge of \( R_c \) approach the edge of input CMRI, \( E^{k+1} \) will obtain its minimum value when area \( R_c \) approaches the optimal endocardium area. So when \( E^{k+1} - E^k < \theta \), with \( \theta \) is defined as an infinitesimal constant, the algorithm is terminated, and the area \( u(x) \) converges to the target chamber area. Figure 3 shows the progress of endocardium contour extraction by improved DM method. And figure 4 shows the distribution matching between the sample chamber area and automatic extracted chamber area.
In Figure 4 (a), (b) and (c), red line is the sample distribution, and blue line is the automatic extraction distribution. From Figure 4 (a) to (c), automatic extraction distribution becomes more and more similar to the sample distribution, which corresponds to progress of Figure 3 (a), (b) and (c) and (d) shows how the energy of grayscale, distance and edge change in each iteration, where red line is the grayscale energy, green line is the distance energy and blue line is the edge energy. Algorithm is terminated after 23 times iteration, when the global energy obtains its minimum. And when we obtain the final endocardium contour, the similarity of grayscale and distance distribution between the sample and automatic extraction result achieves its maximum.

3.2 Improved ACM for epicardium contour extraction

The improved ACM epicardium contour extraction includes two parts: 1) obtain initial iterative curve and edge distribution, and 2) epicardium contour extraction by improved ACM with adaptive changing parameters and a local circular constraint of external force field.

Firstly, the input images are denoised by using Gaussian Core function. Then the improved Canny edge detecting algorithm[18] is used to obtain the optimal edge. Let \( f(x), x \in R^{N \times N} \) be the input image, \( g(x) \) be Gaussian denoising function, and \( j(x) \) be Canny edge detector. We can obtain the edge of the images input like following:

\[
f_d(x) = j(x) * (g(x) * f(x))
\]  

(14)

Let \( f_{end}(x), x \in R^{N \times N} \) be the function of endocardium profile received from section 3.1, we use it with linear sampling to obtain the initial iterative curve of ACM and convert it to be \( w(x) \in [0,1] \). Define \( B \) as \( 3 \times 3 \) dilation template and \( @ \) is dilation operator.

\[
w(x) = w(x) @ B
\]  

(15)

Now we can get \( D_{edge-final}(x,y) \) filtered by \( w(x) \) defined as follows, and the sample results have been presented in Figure 5.

\[
D_{edge-final}(x) = f(x) \cdot [1 - w(x)]
\]  

(16)

Fig.5. Results of middle and base of the heart in two rows: (a) the original images, (b) the chamber images received from section 3.1, (c) the edge images from Gaussian denosing and Canny edge detector, (d) the final edge images for ACM filtered by chamber area, where the red curve is the initial iterative curve.

ACM is a typical application of energy functional optimization problem, which finds minimum of its external and internal energy, as follows, where \( v(s) \) is the active contour curve:

\[
v(s) = \arg\min \int tE_{int}(v(s)) + \tau E_{ext}(v(s))ds
\]  

(17)

We can obtain the external energy \( E_{ext} \) by \( -|\Delta f(x)|^2 \) or by GVF, and get internal energy \( E_{int} \) as following equation, where \( E_{elastic} \) is elastic energy, \( E_{bend} \) is bend energy and \( E_{circle} \) is the proposed local circular constraint energy.

\[
wE_{int} = \alpha E_{elastic} + \beta E_{bend} + \gamma E_{circle}
\]  

(18)

with \( E_{elastic} \) is given by:

\[
E_{elastic} = \frac{|ds|}{dx} - \frac{ds}{dx}
\]  

(19)

and \( E_{bend} \) can be easily calculated by distances between current point and its neighbor points.

\[
\frac{ds}{dx} = \sqrt{1 + y'^2}, \quad \frac{ds}{dx} = \frac{1}{s} \int \sqrt{1 + y'^2} ds
\]  

(20)

Because the shape of left ventricle is something like an oval in base and middle but like a circle in apex, and to make sure the epicardium contour smooth enough, we can use a local circular constraint additionally, as shown in Figure 6. Local circular constraint guarantees that the active contour curve can keep smooth locally, and easily converge to the optimal edge globally.

Therefore, we can get \( E_{circle} \) as equation below, where \( R_0 \) is the radius of the local circle:

\[
E_{circle} = \exp|R_i - R_0|
\]  

(21)

In our experiments, we find that ACM’s iteration is influenced significantly by parameter \( \tau \) of the external force filed. If \( \tau \) is a constant, it will cause a multi-boundary convergence problem, which means that when different edges become close enough, the curve will be only controlled by \( E_{int} \), and \( E_{ext} \) will cut no ice, as shown in Figure 7.

To overcome this problem, an adaptive changing parameter method is developed. Let \( \omega_k \) be the adaptive changing factor, \( x_f \) and \( E_f \) be the position and external energy
where the curve the first time meets a continuous boundary, so we constrain \( \tau^{k+1}_i = \tau^k_i \cdot \omega \) by \( E_{\text{ext}} \) and the distance from \( x_f \), defined as follows:

\[
\omega = \frac{\theta \log E_{\text{ext}}}{\log(||x - x_f||^2 + 1)}
\]

Figure 7. Multi-boundary convergence process. (a) the edge of CMRI. (b) the boundary is very simple at the point m, where the curve can converge to the optimal edge easily. (c) the boundary is complex at the point n. If the parameter is not influenced by different edges, the curve’s changing will be only influenced by the internal force, as a result of which, it will expand to our undesirable edges.

Finally, by Newton iterative algorithm, which considers that the local optimal solution tends to the global optimal solution, we can obtain the epicardium contour \( v(s) \) by calculating the energy of its 24 neighborhood, and consider that the point with the minimum \( E^i \) defined as following can make \( v(s) \) converge to target optimal curve. After repeatedly iterating, when \( v(s) \) almost doesn’t change, our algorithm terminates.

\[
E^i = \alpha E_{\text{elastic}} + \beta E_{\text{circle}} + \tau E_{\text{ext}}
\]

Figure 8 presents the curve convergence procedure controlled by the improved ACM algorithm.

Figure 8. Epicardium contour convergence process. From (a) to (f): the snapshots of left ventricle epicardium contour extraction procedure by the improved ACM algorithm. (f) the result after 53 times iteration, where the red line is the initial iterative curve.

4 Segmentation Experiment

The proposed DM and ACM LV contour extraction methods are evaluated over a dataset which contains about 400 short-axis plane CMRI of over 20 subjects, and compared to other methods.

Figure 9 shows the chamber extraction results of the manual drawing, the proposed method, and methods proposed by Lee et al. [10] and Nambakhsh [14]. Methods mentioned by Lee et al. [10] and Nambakhsh [14] can be used to extracted endocardium contour, but significantly influenced by mastoid muscle and the fuzzy endocardium boundary of the apex. The contour extracted by the proposed method is more distinct, smoother and similar to the manual results.

Figure 10 shows the epicardium extraction results of the proposed algorithm, Lee et al. [10] and Nambakhsh [14] methods, with frames from end-diastole to end-systole, where we use the parameter as: \( \alpha = 0.5, \beta = 0.01, \tau^0 = 0.2 \), the threshold of Canny detector is 0.018, and \( \sigma \) of Guassian Denoising function is 31. Nambakhsh [14]’s method fails to extract a smooth enough contour of epicardium when handling the frames of end-systole. Lee et al. [10]’s method needs complex user input and sometimes can’t obtain the accurate contour if the edge of epicardium is fuzzy or influenced by uneven grayscale distribution. Our approaches do not affected by those factors, and obtains the contour with higher accuracy and high robustness.
We use the following approach to calculate the differences of automatic segmentation method \( s_{\text{auto}} \) with the manual contour \( s_{\text{manual}} \), where \( s_{\text{auto}} (\tilde{x}) \) is the nearest point nearby the line connecting with \( s_{\text{manual}} (x) \) and \( O(x) \), as shown in Figure 11.

\[
h(s_{\text{a}}, s_{\text{m}}) = \frac{1}{N} \sqrt{\sum_{i=1}^{N} (s_{\text{m}}(x) - s_{\text{a}}(x))^2}
\]

The comparison result in Figure 12 shows that the result of the proposed method is the most similar to the manual result where we perform the automatic LV segmentation methods in data of 14 subjects.

After epicardium and endocardium contours segmentation, we can use Simpson method [19] to calculate the cardiac volume to obtain LVEF, defined like following:

\[
V = \sum_{i=1}^{N} h_i \cdot S_i
\]

with \( h_i \) being the thickness of the frames and \( S_i \) being the area of specific frame. And we deploy the results in HF’s early detection with semantically labeling related patient’s information with HF ontologies. The formula below describes how to calculate the LVEF, where \( V \) is the volume of end-diastole, and \( s \) is the volume of systole:

\[
\text{LVEF} = \frac{\text{LVEDV} - \text{LVESV}}{\text{LVEDV}} \times 100\%
\]

Figure 13 shows the LVEF results comparison estimation by linear fitting of the automatic segmentation calculation and the manual drawing results by performing in over 20 subjects (each subject uses about 4*10 frames to calculates the LVEF). The linear fitting equation of manual drawing results and the proposed method is \( y=0.9294x+0.0318 \), and the linear fitting equation of manual drawing results and Lee et al. [10]’s method is \( y=1.1039x-0.0145 \). After comparing with equation \( y=x \), the proposed method is high performance.

5 Conclusions

Based on the computer technology, this study aims to seek an endocardium and epicardium contour extraction method for LVEF calculation from the CMRI, with simpler user interaction, more robust performance, and higher accuracy. More than 20 subjects have been used to demonstrate the method’s performance with comparing to the research results[10] [14] to calculate the endocardium and epicardium contour. Meanwhile, when extracting the epicardium by the improved ACM algorithm, we calculated the differences between the results of manual drawing and the automatic segmentation methods, and a superior performance is revealed by the proposed method. The experiment results show that our method is more efficiently.
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