LEFT VENTRICLE MASS EXTRACTION UTILIZING A MULTI-STEP PROBABILISTIC APPROACH

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ABSTRACT

In this paper, a fully automated multi-step approach for segmenting the Left Ventricle (LV) chamber in echocardiography images is proposed. A preprocessing step is applied to remove the dark background and find the seed point inside the LV chamber, eliminating the specialist intervention for identifying the seed point to initialize the segmentation process. The Rayleigh-Gaussian Mixture model is used to statistically differentiate the blood from the myocardial regions in Echocardiography images. An ellipse inside the LV chamber is then automatically fitted by utilizing the active ellipse model. The resultant ellipse forms the initial contour of the modified B-Spline Snake algorithm that evolves iteratively to outline the inner boundary of the LV chamber. Finally, the Markov Random Field (MRF) algorithm is utilized to extract the LV myocardium. The boundary specified by the B-spline snake is involved in reducing the number of MRF sites. The detected myocardium accuracy for all images is calculated using the dice's coefficient. Our results demonstrate that the proposed method is more reliable and overcomes the common problems in segmentation of Echocardiography images such as speckle noise and large gaps in contrast with previous works.

Index Terms— B-Spline Snake, Active Ellipse Model, Markov Random Field, Expectation Maximization, Echocardiography Images

1. INTRODUCTION

Echocardiography is a valuable non-invasive method extensively used in clinical cardiology. Several clinically important parameters such as cardiac chamber size, wall thickness, cardiac output, ejection fraction and left ventricular mass (LV mass) can be derived from echo images. The automatically detection of LV-mass is unattainable in large-extend due to the complexity. Numerous efforts such as Markov random fields [1, 2], and active contours [3, 4] have been widely used to segment echocardiography images. An effective approach is B-Spline Snake, which has a built-in smoothness requirement, provides faster convergence [5, 6]. MRF offers probabilistic approach which considers neighbor point interactions to overcome local intensity changes [2]. The disadvantage of most previous approaches is that a specialist is required to manually specify the initial contour. Some attempts have been made to automatically find the LV chamber inside the apical images by using morphological operands [7].

In this paper, a combinational approach for segmenting echocardiography images is proposed which utilizes: Active Ellipse Model, B-Spline Snake and Markov Random Field. In addition, a fully automated preprocessing step is used to clip the image to eliminate unnecessary pixels in the wide black area inside the image and to identify the intersection point of 4 chambers. In order to adequately model the intensity of myocardium area versus the blood area, the Rayleigh-Gaussian mixture model is used where its parameters are estimated for each individual image using the expectation maximization method. The preprocessing step is crucial since the uninformative dark background of the image with low intensities can majorly disturb our intensity based mixture model calculation. The Rayleigh-Gaussian mixture model is used in the active ellipse model and also to derive the MRF model. The use of the mixture model and the expectation maximization leads to achieve a better performance in this paper over our previously reported results [2]. The active ellipse model [8] is applied to automatically find a suitable ellipse inside the LV chamber, eliminating the specialist intervention for initializing the segmentation process. Afterwards the resultant ellipse forms the initial contour of the B-Spline Snake which extracts the LV chamber boundary. Finally, the LV myocardium is detected using the Markov Random Field (MRF) technique.

This paper is categorized into four sections as follows: Section 1 is the introduction. In section 2 we discuss the details of our methodologies. The acquired results are presented in section 3. The conclusions and a brief perspective of our approach are provided in section 4.

2. METHODOLOGY

2.1. Preprocessing Step

This step constitutes of two parts. In the first part the uninformative area of the image is eliminated and in the second part, the intersection point of 4 chambers is located. The intersection point is used in the Active Ellipse Model to place the seed point for the ellipse inside the LV chamber. The background in the ultrasound images forms a big portion of the image which does not contain valuable data. Moreover, the background containing lots of pixels with low

intensities may greatly affect the calculation of Rayleigh-Gaussian model. To overcome this issue, we have proposed a simple and effective technique to remove the undesired pixels. In an iteratively process, two vertical lines, each broken down to two connected parts, move from the right and left side of the image toward the center. As each fragment approaches the outer edges of informative data, pyramidal shape, it stops moving toward the center and the other fragments maintain their movement flexibly (Fig 1). The process continues until the entire lines frame the pyramid in the image.

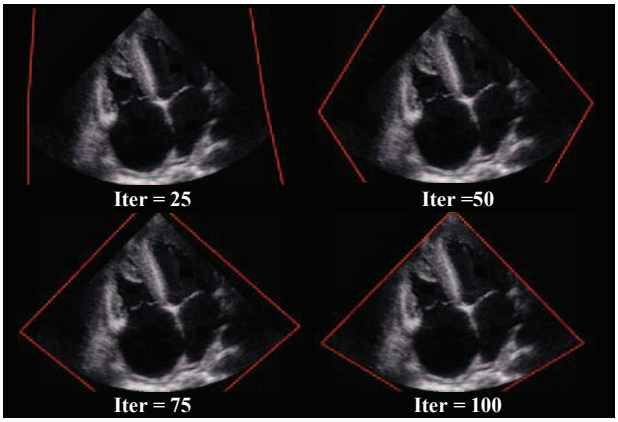

Fig 1. Demonstration of the performance of the proposed algorithm to find an approximation of the echo pyramid.

In the second step of the preprocessing a new method is developed to find the intersection point. Two vertical and horizontal patterns are convolved into the image in 4 scales from finest to coarsest. In this procedure the vertical myocardium wall between the left and right chamber (Fig 2.a) and the horizontal wall between atriums and ventricles (Fig 2.b) are detected. Interpolating the detected horizontal and vertical points, the equations of the lines are estimated. Using the defined equations the intersection point is easily determined. (Fig 2.c)

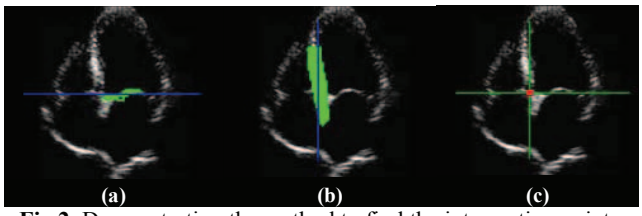

Fig 2. Demonstrating the method to find the intersection point.

2.2. Rayleigh-Gaussian Mixture Model and Expectation Maximization

The Rayleigh-Gaussian mixture model is employed to identify a parametric model for both the blood and myocardium regions in images. The blood and myocardium regions are modeled respectively as the Gaussian and Rayleigh distributions. The mixture model is calculated according to the histogram of images. As each image has different histogram, this step should be applied for each image independently. The mixture model is needed for defining forces of the Active Ellipse model; it is also necessary for deriving the MRF equations (presented later in section E). In the following, the mixture models are formulated and the estimation method is described in detail. A set of pixel intensities is defined as: $X = \{x_i \mid i = 1,..,N\}$, taken from the inside of the pyramid in the ultrasound echocardiograph image. The following describes the mixture of K classes of distributions:

$$P(x_i \mid \Psi) = \sum_{j=1}^{K} p(x_i;\sigma_j)\theta_j \qquad (1)$$

where $p(x_i;\sigma_j)$ is the probability density function and $\Psi = \{\psi_1, \psi_2, ..., \psi_k\}$ is a set of mixture parameters to be estimated. $\psi_k = \{\theta_k, \sigma_k\}$ consists of prior probabilities and density function parameters. Due to the independence and uniform distribution of the pixel intensities, the joint distribution of the pixels can be written as:

$$P(X \mid \Psi) = \prod_{i=1}^{N} \sum_{j=1}^{k} p(x_i;\sigma_j)\theta_j \qquad (2)$$

To convert the products into the summation of terms, we simply take the log of the function:

$$\lambda(X,\Psi) = \log P(X \mid \Psi) = \sum_{i=1}^{N} \log\left(\sum_{j=1}^{K} p(x_i;\sigma_j)\theta_j \right) \qquad (3)$$

$\lambda(X,\Psi)$ is defined as the likelihood function. In the next step, Ψ is estimated in such a way that the likelihood function is maximized. Using the Jensen`s inequality, we can write the equation (4) as:

$$\lambda(X,\Psi) \geq \sum_{i=1}^{N}\sum_{j=1}^{K} \gamma_{i,j} \log\left(p(x_i;\sigma_j)\theta_j / \gamma_{i,j} \right) \qquad (4)$$

$$\gamma_{i,j} = p(x_i;\sigma_j)\theta_j \Big/ \sum_{m=1}^{K} p(x_i;\sigma_m)\theta_m, \sum_{j=1}^{K} \gamma_{i,j} = 1 \qquad (5)$$

$\gamma_{i,j}$ is a constant which acts as a normalizing factor. Finding the conditions that maximize the right hand of the inequality of equation (4), the distributions that models the K classes in the best form, is obtained.

$$\beta(\sigma,\theta) = \sum_{i=1}^{N}\sum_{j=1}^{K} \gamma_{i,j} \log p(x_i,\sigma_j) + \sum_{i=1}^{N}\sum_{j=1}^{K} \gamma_{i,j} \log \theta_j \qquad (6)$$

In order to maximize $\beta(\sigma,\theta)$ the first term must be maximized with respect to σ and the second term with respect to θ, which is identically defined for all mixture combinations with the aid of Lagrange method.

$$L(\theta) = \sum_{i=1}^{N}\sum_{j=1}^{K} \gamma_{i,j} \log(\theta_j) - \lambda\left(\sum_{j=1}^{K} \theta_j - 1\right), condition: \sum_{j=1}^{K} \theta_j = 1 \qquad (7)$$

To maximize the first term, its derivation is set to zero.

$$\frac{\partial L(\theta)}{\theta_m} = \sum_{i=1}^{N} \gamma_{i,m} \frac{1}{\theta_m} - \lambda = 0 \qquad (8)$$

From (8), $\hat{\theta}_j$ is estimated as:

$$\hat{\theta}_j = \frac{1}{N}\sum_{i=1}^{N}\gamma_{ij} \quad (9)$$

The first density function is Gaussian distribution which is used to model the myocardium region intensity, as:

$$p(x;\mu_{myo},\sigma_{myo}) = \frac{1}{\sqrt{2\pi\sigma_{myo}^{\ 2}}} e^{\frac{-(x_i-\mu_{myo})^2}{2\sigma_{myo}^{\ 2}}} \quad (10)$$

The Gaussian distribution has two parameters, mean and standard deviation, which should be obtained by maximizing the equation as follows:

$$\beta'(\mu_{myo},\sigma_{myo}) = \sum_{i=1}^{N}\sum_{j=1}^{K}\gamma_{i,j}\log(\frac{1}{\sqrt{2\pi\sigma_j^{\ 2}}} e^{\frac{-(x_i-\mu_j)^2}{2\sigma_j^{\ 2}}}) \quad (11)$$

By getting the first derivation for μ_{myo} and σ_{myo}, and setting them equal to zero, the two parameters are estimated as:

$$\sigma_{myo} = \sqrt{\sum_{i=1}^{N}\gamma_{i,m}(x_i-\mu_{myo})^2 \Big/ \sum_{i=1}^{N}\gamma_{i,m}}$$
$$\mu_{myo} = \sum_{i=1}^{N}\gamma_{i,m}x_i \Big/ \sum_{i=1}^{N}\gamma_{i,m} \quad (12)$$

The Rayleigh distribution is used to model the blood region intensity and can be calculated as below:

$$p(x;\sigma_b) = \frac{x}{\sigma_b^{\ 2}} e^{\frac{-x^2}{2\sigma^2}}, \sigma_b = \sqrt{\sum_i \gamma_{i,m}\frac{x_i^2}{2} \Big/ \sum_i \gamma_{i,m}} \quad (13)$$

Thus σ_b differs among Echocardiography images.

2.3. Active Ellipse Model

Active ellipse model is developed to locate LV chamber in apical chamber views. The intersection point was previously detected in the preprocessing step. A small ellipse is then placed on top-left side of the intersection point of the chambers. The ellipse grows iteratively to fit the chamber. The reader is encouraged to refer to [8] for a comprehensive introduction. In this section, we only expand on modifications performed in this work which involves the Rayleigh-Gaussian mixture for calculating forces. The evolution of the ellipse is determined with interaction of internal and external forces. The internal force enables the growth and the external one enforces the evolving ellipse to cease in the adjacent of the actual boundary inside the chamber. In the previous work [8], the Gaussian model was used for the myocardium and it was a fix value for all images. An advantage in this work, over our previous approach [8], is that the Gaussian distribution model is individually calculated for each image (Section 2.2).

2.4. Modified B-Spline Snake

The B-Spline Snake model is an active contour model which is used in this work to extract the inner-boundary of the LV chamber. The contour is represented by B-Spline basis functions and a set of control points govern the deformation of the contour in interaction with image forces [2]. The fitted ellipse obtained in the previous step is used to form the initial contour of the B-Spline Snake model and it has an important impact on the convergence time of the B-Spline Snake. The closer the initial contour is to the boundaries, the less iterations it takes for the B-Spline Snake to converge. The reader is referred to [2] for further information.

2.5. Markov Random Field

The MRF is a statistical approach based on the Bayesian framework which is used to segment the LV myocardium [2]. It turns the global definition of the prior probability to a local representation for each pixel based on its surrounding neighbors, leading to achieve more robustness in presence of myocardium intensity changes. It constitutes of sites, S, placed on radial rays drawn from the center of the fitted-ellipse. The detected boundary (section 2.4) is used to remove sites placed inside the LV chamber, aim to reduce the number of sites. The MRF consist of two random fields assigned for sites, *X* and *Y*. The first one is the observations field which contains the image data at site locations, $Y = \{Y_s, s \in S\}$ and $Y_s \in \{0,...,255\}$. The second one is the labels field, $X = \{X_s, s \in S\}$ and $X_s \in \{e_{-1} : blood, e_1 : myo\}$. All sites are initiated as the blood area. The a-posterior probability is calculated for two assumptions: 1) blood, 2) myocardium. The conditional probabilities are considered as the Rayleigh and Gaussian distributions for the blood and myocardium, respectively.

$$p(Y \mid X = e_{-1}) = \frac{y}{\sigma_b}\exp(-\frac{y^2}{2\sigma_b^2}) \quad (15)$$

$$p(Y \mid X = e_1) = \frac{1}{\sqrt{2\pi}\sigma_m}\exp(-\frac{(y-\mu_m)^2}{2\sigma_m^2}) \quad (16)$$

The prior-probability is modeled as the Gibbs distribution [2]. The site is labeled according to the greater a-posterior probability and is iteratively repeated for all sites until the result converges.

3. RESULTS

The proposed method is implemented in MATLAB7.10 environment using a PC with Intel I7 Processor and 4 GB of Memory. Images are acquired using a Pinnacle capture card from a VIVID3 echocardiography instrument. To evaluate the method, twenty images of four chamber views are gathered from clinical cases with pre-defined ground truths. The detected myocardium accuracy is calculated using the dice's coefficient [9]. The preprocessing step increases the accuracy of the proposed method by reducing the error of the calculated mixture model from 26.1% to 4.9% (Fig 3).

Table 1 demonstrates that the proposed method offers higher accuracy and speed of convergence as compared to the previously reported approach [1], [2].

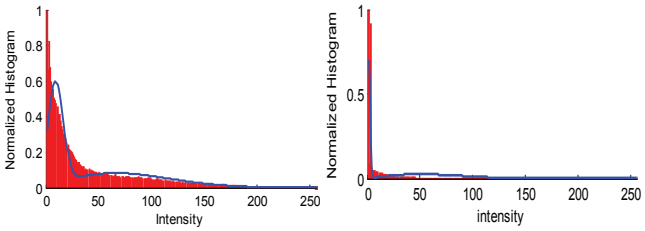

Fig 3. The left figure shows the histogram (red) and the mixture model (blue) with the preprocessing step. The right figure shows it without considering the preprocessing step.

The accuracy of the proposed method is higher than the presented work in [1] because of using the Rayleigh-Gaussian model instead of the Gaussian-Gaussian mixture model. The presented work shows better accuracy in contrast with our previous work, because of using Expectation Maximization and finding mixture model parameters individually for each image. The result of the computation time is measured as the sum of the B-Spline Snake and MRF. The preprocessing step, Expectation Maximization and Active Ellipse Model normally takes about one tenth of the above computation time, however they are not included.

Table 1. Comparison of new approach and previous approach according to the Dice's Coefficient and Computational time.

#	Method	Dice's Coeff (%)	Compute Time (sec)
1	Previous Approach [2]	92.12±4.61	1.12±0.65
2	Markovian Level Set [1]	92.95±2.16	1.80±1.53
3	Proposed Approach	94.30±3.79	0.86±0.31

The multi-step segmentation process is shown in the (Fig 4). The result is demonstrated in the right-bottom image (Area encompassed by the green boundary) which is obtained by smoothing the result of the MRF method (Bottom-Left).

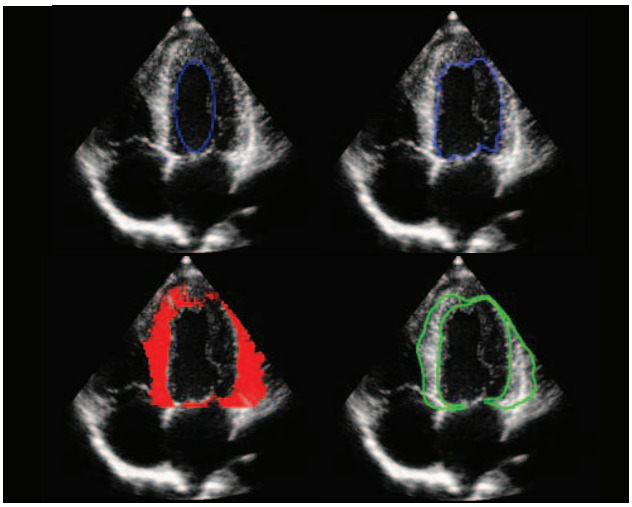

Fig 4. Demonstration of the result of Active Ellipse Model (Top-Left), B-Spline Snake (Top-Right), MRF (Bottom-Left) and Final Result (Bottom-Right).

4. CONCLOUSION

This paper presented a novel image segmentation algorithm for the LV myocardium extraction in the echocardiography images. In the first preprocessing step the uninformative data are trimmed out to speed up the process while achieving more accurate statistical representation. The obtained intersection point in the second preprocessing step eliminates the specialist's intervention and is used as the initial seed point of the Active Ellipse Model. The Rayleigh-Gaussian mixture model presents two distributions to distinguish between the blood and myocardium regions. Echocardiography images highly differ in the myocardium intensity and the noise level. Thus, the expectation maximization method is individually applied for each image to maintain a proper statistical presentation. The application of the algorithm has been demonstrated and evaluated for various echocardiography images. While maintaining excellent accuracy in extracting details of cavity contours, the algorithm also takes into account the gaps on the chamber walls and provides smooth segmentation results.

5. REFERENCES

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