A Novel Method for Left Ventricle Volume Measurement on Short Axis MRI Images Based on Deformable Superellipses

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Abstract. Diagnosis and treatment follow-up of cardiac diseases can rely on numerous cardiac imaging modalities. Among these modalities Cardiac Magnetic Resonance (CMR) has become a reference examination for cardiac morphology, function and perfusion in humans. It is the current reference standard for the assessment of both left and right ventricular volumes and mass. There are numerous automatic and semi-automatic methods for cardiac cavities segmentation and volume measurement but the problem is still open. In this paper a novel semi automatic method is proposed based on parametric model, superellipse, for segmentation and measurement the volume of the left ventricle on short axis MRI images. For fitting superellipse on MR images, a set of data points has been needed as a partial data. These data points are been provided by user and this fact put our method in the category of semi-automatic methods.

Keywords: Left ventricle, Volume measurement, Short axis cardiac MR, Superellipse, Levenberg Marquardt algorithm.

1 Introduction

In recent years Magnetic Resonance Imaging (MRI) has become a reference standard examination for cardiac morphology, function and perfusion in humans [1]. Accurate segmentation of the Left Ventricle (LV) endo- and epicardium boundaries and determination of the volume of ventricular chambers at different phases of the cardiac cycle in 2D cardiac Magnetic Resonance sequences is needed for assessment of ventricular function. The segmentation of these images provides clinically useful indicators of heart function, such as End-systolic volume (ESV), End-diastolic volume (EDV), the ejection fraction (EF) ratio and Myocardial mass.

The segmentation and volume measurement of cardiac chambers is currently performed manually in clinical routine. This long and tedious task, prone to intra- and inter-expert variability, requires about 20 min per ventricle by an expert clinician. The great need for automated methods has led to the development of a wide variety of

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segmentation methods [2], for example thresholding [3], pixel classification [4, 5], deformable models and model based segmentation. In left ventricle volume measurement area several works have been performed in literature. Ranganath [6] performed an automatic contour extraction of left ventricular contours from cardiac MRI studies. These algorithms were based on active contour models incorporating contour propagation. Goshtasby et al. [7] applied a two-stage algorithm for extraction of the ventricular chambers in flow-enhanced MR images. They approximate location and size of endocardialy surfaces by intensity thresholding and reposition points on the approximated surfaces to nearest local gradient maxima. Then they fit a cylinder into the point set. A comprehensive review of segmentation methods in short axis cardiac MR images can be found in [1]. In this paper, a parametric superellipse model is used, for fitting on left ventricle in short axis cardiac MRI images. Superellipses are a flexible representation that naturally generalizes ellipses. They can model a large variety of natural shapes, including ellipse, rectangles, parallelograms, and pinched diamonds, by changing a small number of parameters [8, 9]. Superellipses were first formulated by Gardiner [10]. Several approaches have been suggested to determine the parameters of superellipses and approximately all of them need data points for fitting superellipse on them. In the next step using Levenberg-Marquardt algorithm [11] (LMA) for parameter estimation superellipse has been fitted on data points. The final step is the estimation of left ventricle volume which is done by means of generating a superellipsoid from fitted superellipses on each slice.

2 Superellipse Fitting

Superellipses are a flexible representation that can model a large variety of natural shapes, including ellipse, rectangles, diamonds, and pinched diamonds, by changing a small number of parameters. A centered superellipse can be defined in a parametric form by:

$$\left(\frac{x}{a}\right)^{2/\varepsilon} + \left(\frac{y}{b}\right)^{2/\varepsilon} = 1 \tag{1}$$

where, squareness parameter $\varepsilon > 0$ specifies the squareness in 2-D plane and (a,b) are the length of semi axes.

Several methods have been proposed for fitting superellipses to the images [12]. An iterative Levenberg-Marquardt algorithm [11] (LMA) is used in this paper for parameter estimation.

Fitting superellipse on a given set of pixel data using least square solution (LMA) achieved by finding the set of model parameters that minimize the sum of the squares of the distances between the model curve and given pixel data. The notion of distance can be interpreted in various ways and Rosin and West [13] investigate several examples. A simple but still effective measure is the algebraic distance given by

$$Q_0(x,y) = \left[\frac{(x-x_c)\cos\theta - (y-y_c)\sin\theta}{a}\right]^{2/\varepsilon} + \left[\frac{(y-y_c)\cos\theta - (x-x_c)\sin\theta}{b}\right]^{2/\varepsilon} - 1 \tag{2}$$

One of the main problems with the algebraic distance is that it results in different distance estimates for different parts of superellipse curves depending on the local curvature of the curve. This is because the conventional algebraic distance measure treats pixels as individual data points and relations between pixels are not exploited. In this paper we propose a modification procedure using adaptive data point selection and parameter λ for more effective convergence of LMA algorithm.

2.1 Fitting Procedure

Like other numeric minimization algorithms, the Levenberg–Marquardt algorithm is an iterative procedure. To start a minimization, the user has to provide an initial guess for the parameter vector, β [11]. In many cases, an uninformed standard guess like β = (1, 1, ... , 1) will work fine; in other cases, the algorithm converges only if the initial guess is close to the final solution.

So our fitting procedure consists of 3 steps:

1. Preparing initial values for Levenberg Marquardt algorithm namely x_c, y_c, a, b, ε, θ, t. Our parameter vector, therefore should be expressed as β { x_c, y_c, a, b, ε, θ, t}

2. Determining data points. These pixels used as prior knowledge for superellipse fitting.

3. Implementation of Levenberg Marquardt algorithm for finding superellipse parameters.

The initial values are given by user. For our propose an uninformed standard guess like β = (1, 1,..., 1) will work fine. Also data points are given by user. After determining data points the Levenberg Marquardt algorithm starts fitting superellipse to partial data. First of all as a problem definition there are a set of data points of independent and dependent variables, (x_i, y_i), optimize the parameters β of the model curve f(x, β) so that the sum of the squares of the deviations

$$S(\beta) = \sum_{i=1}^{m} \left[y_i - f(x_i, \beta) \right]^2 \tag{3}$$

becomes minimal. Levenberg Marquardt algorithm as mentioned is an iterative procedure and needs initial values for parameter vector β.

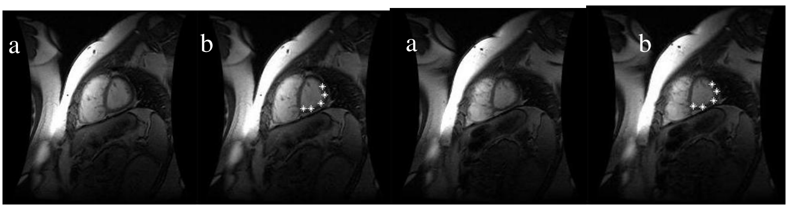

Fig. 1. (a) Original CMR image (b) Determined initial data point on image

After preparing theses initial values by user algorithm starts its iteration. In each iteration step, the parameter vector, β, is replaced by a new estimate, β + δ.To determine δ, the functions $f(x_i, \beta + \delta)$ are added by $J_i \delta$, Where

$$J_i = \frac{\partial f(x_i, \beta)}{\partial \beta} \tag{4}$$

is the gradient (row-vector in this case) of f respect to β. At a minimum of the sum of squares, called S, the gradient of S with respect to δ is 0. Differentiating the squares in the definition of S, using the above first-order approximation of $f(x_i, \beta + \delta)$, and setting the result leads to:

$$(J^T J + \lambda I)\delta = J^T [y - f(\beta)] \tag{5}$$

where J is the Jacobean matrix whose i[th] row equals J_i, f and y are vectors with i[th] component $f(x_i, \beta)$ and y_i, respectively, I is the identity matrix, giving as the increment, δ, to the estimated parameter vector, β. And finally the (non-negative) damping factor, λ, is adjusted at each iteration. If reduction of S is rapid, a smaller value can be used, whereas if iteration gives insufficient reduction in the residual, λ can be increased. The result of using this algorithm on short axis cardiac MRI can be seen in Fig. 2.

3 3-D Visualization and Estimation of LV Volume

The final step is the calculation of the left ventricle volume. Therefore the segmented pixels of all images are counted and multiplied by their voxel size.

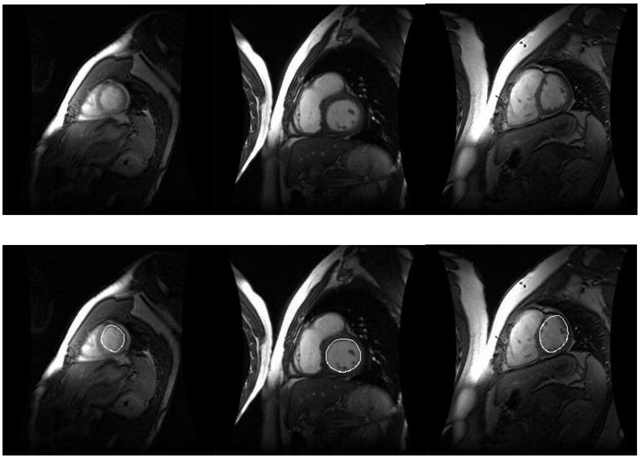

Fig. 2. Result of superellipse fitting on some slices of short axis cardiac MRI images of various patients. Original images (top row) and superellipse fitting result (bottom row).

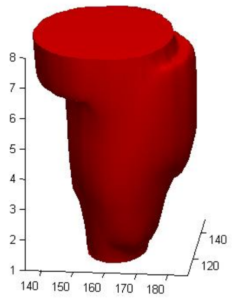

Fig. 3. 3-D visualization of LV generated from superellipse fitted on short axis plane

The averaged volume is multiplied by the voxel size pixel_spacing_x * pixel_spacing_y * slice_gap and added to the other slices for the final volume. The volume generated for this approach can be seen in Fig. 3.

4 Experimental Results

End-diastolic and end-systolic volumes are clinically important parameters in cardiac ventricular function assessment. So, some of our results in this area are provided here.

Table 1 shows all of the provided information of the image data sets. Columns"EDV1" and"ESV1" contain the results of the parametric volume estimation while columns"EDV2" and"ESV2" contain the older results of the parametric model from the actual patient examination. Our method is tested in 33 image datasets. Our results show better fitting compared to ellipse fitting methods for segmenting left ventricle. This is because of the nature of superellipses that cover a wider range of shapes and consequently our results is closer to the left ventricle borders. As a quantitative comparison, Computational cost reduced in our proposed method, for example 1.3 times faster than [14].

We used Similarity and Specifity index for evaluate our method validation and obtained 88.3% and 85.6% for them.

Table 1. Patients datasets with volume estimation results from the superellipse model

P.Num	EDV1[ml]	ESV1[ml]	EDV2[ml]	ESV2[ml]
1	88.4	24.6	85.1	23
2	69.1	20.2	72.4	22
3	83.2	24.6	88	26.6
4	81.3	10.8	79.9	12.2
5	74.2	27	72	27.7

5 Conclusion

In this paper, a semi- automatic method is proposed for segmentation and measuring the volume of left ventricle. Superellipse models are used for fitting on left ventricle in the short axis cardiac MR images, volume measurement of left ventricle and making a 3-D model of it. Superellipse fitting methods need partial data. These partial data are been gotten from user and this fact put our method in the category of semi-automatic methods. Future works can focus on generation of partial data automatically on the basis of cardiac short axis MR image features.

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