A Unified Automated Segmentation Technique for the Left Ventricle Segmentation in Cardiac MRI

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Abstract. Though the technology updated for every minute of time to aid all kinds of problems facing in every day practical life, the technique requires amelioration to solve or support specific kinds of problems like early identification of cardiovascular disease. For the past decades, cardiovascular diseases (CVD) are the major reason for death. Cardiac MRI is useful for acquiring the anatomical data of the alive heart for the clinical diagnosis of cardiovascular diseases. From the LV Segmentation on cardiac MRI, the important parameters estimated to diagnose are ejection fraction, left ventricle myocardium mass, stroke volume, etc. Hence segmenting the LV automatically plays a significant role in helping the physician to test cardiac functions quickly since manual segmentation is a time-consuming work. This Automatic Segmentation also eliminates manual errors during evaluation. Therefore, to discuss the problem we propose enhanced techniques that is a unified method to segment the left ventricle automatically from the cardiac MRI image. The algorithm demonstrated in this work is to combine existing segmentations in an efficient way to give even more efficient and accurate results.

Two performance evaluation techniques namely APD and DICE to quantify the result. Outcomes obtained are then compared with recent segmentation methods to show the efficiency of the unified segmentation technique.

Keywords: Intensity inhomogeneity, Bias field Correction, Level set, Energy pre-fitting, APD, DICE, OTSU threshold.

1. Introduction

From the statistics of WHO, all around the world, it is evaluated that ischemic cardiac diseases and cardiac stroke are the major cause of the rise in mortality rate [1]. It is predicted that by the year 2030, a population of 23.3 million people would be affected by CVD’s. One of the solutions to reduce the effect of ischemic CVD is to isolate the problem at the earliest and require a medical diagnosis, in which, every chamber of the heart is scanned and undergo segmentation of the desired region to diagnose at precise. There are many modalities to monitor and diagnose the CVD’s which include Echocardiogram, Blood tests, coronary angiography, radionuclide tests, X-rays, electrocardiogram (ECG), positron emission tomography (PET), MRI scans, CT scans, etc.[2] Among all the modalities, MRI has its own benefits as it provides enough information on the functions of the heart such as morphology, contractions of tissue, blood flow, etc.

The spatial resolution of MRI provides better visualization than other imaging modalities. The
major technological benefit of MRI is that it can depict and differentiate among tissues using their physical and biochemical properties. Accounting to all the advantages of MRI, it is established as the research gold standard with improved clinical impact. In the process of diagnosis, the next pace followed by imaging is to find the desired ROI. Selecting the desired ROI requires an explicit analysis of the anatomy of the heart and its chambers including some parameters that determine the well-being of a human. As we knew the heart contains four chambers,[3] they are right and left atrium and right and left ventricles. Ventricles play a major in pumping the oxygenated blood from the heart to all other organs of the body whereas arteries receive the deoxygenated blood from other organs to the heart. Therefore, it is significant to segment the ventricles to analyze the functioning of the heart where segmentation is the method of partitioning a particular segment or region from a digital image depending on some of the characteristics or properties of an image such as pixel, color, intensity, texture, foreground and background differences, etc. The traditional way of segmentation is done manually by the clinicians or doctors based on their experience which is referred to as ground plane. But the manual segmentation or delineation on multiple slices and segments is a tedious and time-consuming process. To overcome this, there are various semi-automated and fully automated segmentation methods emerging in practice overcoming the limitations from one to the other.

Currently, there are various segmentation algorithms [4] in an application such as active contour, level set, thresholding algorithms, methods based on entropy, clustering algorithms, and many. These methods contain the knowledge of delineating the boundaries of the heart more objectively than manual contouring. In general, both the semi-automatic and fully automatic segmentation fall into two classifications: (1) model-driven approaches based on strong prior knowledge, (2) image-driven approaches without or with weak prior knowledge. Thresholding, region-based growing, clustering, pixel classification, active contours are some of the typical image-driven techniques. The combinations of techniques are also used to localize the initial contour or seed point with a low-intensity level. Therefore, there is a wide range of techniques used for cardiac MRI segmentation. Thus, the choice of selecting an approach or the combination of those is trivial. Some parameters are needed to be considered to choose a technique. Two important considerations are the technique should be constrained by the specific procedure and availability of large training datasets. In a similar context, a method is proposed to overcome such limitations that prominently occur during segmentation. The two limitations are intensity inhomogeneity and initializing a contour. The proposed method is a unification of three different methods that help to (i) handles the intensity inhomogeneity (ii) finds initial contour through thresholding and finally segments based on energy fitting. Each of these methods exhibits its significant role in obtaining better results.

Organization of the paper as follows. Section 2 briefs the related work to the proposed method, Section 3 gives the details of the proposed method which is a unified model that first removes the intensity inhomogeneity then finds the initial contour using the OTSU method, and finally segments the left ventricle based on energy pre-fitting. Section 4 discus the result and compares it with existing methods and Section 5 finally concludes the work then references.

2. Related Work
There are many semi-automated and fully automated segmentation techniques in practice. Some of those are considered as a back path to the proposed method and are demonstrated as follows.

2.1 Active contour model with Global minimization for segmentation
Active contour (AC) models are majorly used in image segmentation but has the drawback of local minimum that leads unsatisfactory result due the difficulty in the initial contour. To address this initial contour problems [12] proposed a unified model by combining AC model, denoising and Mumford-shah model and It solves the global minimization problem in a unique way. The model defines the energy functional based on dual formulation
\[ \min \{ E(u, \lambda) = \int_{\Omega} g(x) \nabla u \, dx + \lambda \int_{\Omega} |u - f| \, dx \} \] (1)

And based on Mumford shah – model, the energy is defined as
\[ \min_{C, c_1, c_2} \left\{ E = \text{Length}(C) + \alpha \int_{\Omega} (u - c_1)^2 \, dx + \beta \int_{\Omega \setminus C} (u - c_2)^2 \, dx \right\} \] (2)

Where, \( \alpha \) and \( \beta \) are positive constant, \( u \) - original image, \( c_1 \) and \( c_2 \) constant that are calculated within the region and outside the region bounded by the \( C \)

By minimizing the energy, the method proposed in [12] results a good segmentation and has proved its efficiency in segmentation of real-world images and medical images as well. Figure 1. Shows the outcome of [12] for a selected slice.

2.2 Level set method and Bias correction

The algorithm proposed in [7] image observed \( u \) is modelled as the multiplicative components given in the equation
\[ u = BI + \eta \] (3)

Where,
\( u \) is output of imaging device, \( I \) - is true image, \( B \) - multiplicative component reflects the intensity inhomogeneity and \( \eta \) – added noise with observed image \( I \)

The energy defined is given by
\[ E = \int \left( \sum_{i=1}^{N} \int_{\Omega^i} K(y-x \mid u(x) - B(y)c_i^2) \, dx \right) \, dy \] (4)

Where, \( k \)- kernel function,
\[ k = \begin{cases} \frac{1}{\alpha} e^{-\frac{|u|^2}{2\sigma^2}}, & \text{for } |u| \leq \rho, \\ 0, & \text{otherwise} \end{cases} \] (5)

\( \rho \) – is the neighbourhood radius, by minimizing the energy \( E \), both estimation of bias field and Segmentation are obtained. For the detail of minimization of \( E \) with respect to the constants and bias field readers are referred to [7]. Figure 2. Shows the outcome of [7] for a selected slice.

2.3 Local Region Fitting Energy for Active Contour model

Since many of the active contour models that are based on energy minimization fails to give proper segmentation result due the inappropriate initialization further it stuck at local minimum. Both of these two problems are addressed in [14], it is also energy minimization based active contour model, that uses an idea of keeping the fitting energy values always higher inside the contour and lower outside the contour.
This idea not only reduces the problem of local minima and also improves the segmentation result. To have the proper direction of curve evaluation [14] defines two fitting functions $f_1$ and $f_2$ and used min and max function to exchange the values of these two fitting functions whenever required. Figure 3. Shows the outcome of [12] for a selected slice.

That is

$$f_1_{\text{new}}(x) = \min (f_1(x), f_2(x)) \text{ and } f_2_{\text{new}} = \max (f_1(x), f_2(x))$$

(6)

### 2.4 Active contour model with local Pre-fitting energy

The main aim of [13] is to improve the segmentation speed at the same time tackling the intensity inhomogeneity and local minima problem. It defines the fitting functions from the average values of local image intensities before the actual cure evolution. The overall energy functional proposed by [13] by

$$F_{lpf} = \text{Local pre-fitting energy } (E_{LPF}(C)) + \alpha \text{ Length term } (L(\phi)) + \beta \text{ Regularized term } (P(\phi))$$

(7)

Where, $\alpha$ and $\beta$ are positive constant.

The local pre-fitting energy is given by

$$F_{lpf} = \text{Local pre-fitting energy } (E_{LPF}(C)) + \alpha \text{ Length term } (L(\phi)) + \beta \text{ Regularized term } (P(\phi))$$

(8)

The length and regularized term respectively are defined as

$$L(\phi) = \int \delta(\phi) |\nabla \phi| dx \text{ and } P(\phi) = \int \frac{1}{2} (|\nabla \phi| - 1)^2 dx$$

(9)

The introduction of pre-fitting functions increases the segmentation speed and robust to the initial contour. Figure 4. Shows the outcome of [12] for a selected slice.

### 2.5 Otsu’s Thresholding Method

Otsu’s method is one of the finest methods that can convert a gray color image to binary (foreground and background) [10]. This method sets an initial local value, that can lower the intra-class variance or maximize the inter-class variance [11]. The function that gives the intra-class variance defined as

$$\sigma^2_t = \omega_1(t)\sigma^2_t + \omega_2(t)\sigma^2_t$$

(10)

The OTSU method does iteration in all possible threshold values and calculates the measure of the spread of pixel levels at each side of the threshold that is the pixel that either falls in the
foreground or background. The goal is to find the value of the threshold where the sum of foreground and background spreads at its least. It minimizes the weighted within the class variance. To overcome the limitations in traditional Otsu’s method, two-dimensional adaptive thresholding [12] has also been proposed. In summary, each method has its own strength in segmenting the left ventricle. And all the methods use a few initial values. The change of those initial values when the curve deviates from the ground truth is necessary. These deviations are due to (i) intensity in-homogeneity, (ii) improper initialization of level curve. To solve these two problems simultaneously we are unifying the active contour methods and trying to avoid the change of initial values from time to time and to have the correct segmentation results. The result and discussion section highlight the performance improvement of the unified method in terms of evaluation parameters.

3. Proposed method
The proposed method, the block diagram is shown in figure 5, is the unification of three different segmentation methods they are level set[8, 9] evolution method to remove intensity in-homogeneities in the image and bias field estimation for bias field correction, Otsu’s thresholding which plays a significant role in initializing a contour and active contour using energy fitting model[13] in the final step of segmentation process. The image sequence undergoing the process of segmentation is shown in the above block diagram. To understand this in a better way, the process to be described in a reverse manner i.e. from the active contour. Li et al. proposed an active contour model with a region-scalable fitting (RSF) energy [14]. This model can effectively segment the images with intensity in-homogeneity. But the real problem occurs in setting the initial contour appropriately. Since the energy function is non-convex, the RSF model stuck in local minima. Besides that, the time cost is also high. To overcome this challenge, Zhang et al. [16] presented an active contour model based on local image fitting (LIF) energy [15]. compared to the RSF model, the computational cost of the LIF model [16] is smaller because LIF has only two convolutions that are computed in each iteration and uses the Gaussian kernel function. This model runs iteratively throughout the process and the samples of iterations are shown in figure 6. An improved model was proposed by Zhang[17] which driven by local image fitting. However, the problem of initial contours has not been solved. Otsu’s adaptive thresholding plays a significant role in setting an initial contour. This is one of the simplest methods to set an initial contour by minimizing or maximizing class variances. The equation (3) defines a function to carry out the variance computation and update the threshold value by comparing the spatial properties of one pixel to its neighboring pixels. But in practice, Otsu’s method works well for an image with fewer intensity in-homogeneities. The parameters to set an initial contour are as follows:

Distance regulation term \( \mu = 1; \ \nu = 0.001A^*A; \ \sigma = 2; \) and time step, \( \Delta t = 0.2 \). where A is normalization constant equal to 255.
The main principle of Otsu’s method is to convert a grayscale image (colored) to a binary image (0’s and 1’s) which may result in erroneous outcomes if the level of intensity in-homogeneity is high and therefore, to reduce the in-homogeneities in an image, a level set evolution segmentation method is performed to the input image. The level method also involves the correction of bias field which may corrupt the image. Intensity inhomogeneity correct image is shown in figure 7.

After the establishment of the initial contour, segmentation is done using the Active contour model based on local pre-fitting energy. This method segments the image within a less computational time. Two pre-fitting functions are defined on the two sides of the curve by locally approximating the average intensities before the evolution of the curve. Since pre-fitting functions are defined before the curve evolution there is no need for updating at each iteration. The energy obtained based on local pre-fitting function is termed as LPF Energy.

Then this energy is incorporated into the variational level set formulation with a length constraint term and a distance regularized term. In our method, the length term and distance regularization term are given as $v = 0.0001 \cdot A^2$ and $\mu = 1$ respectively where $A$ is the normalization constant equal to 255. This length and distance regularization term used for smoothing the curve and it eliminates the curve outside the boundary. And other parameters initialized are $\lambda$ which is 1 and epsilon which also 1, the number of iterations given is 100, and to control the size sigma is set to 2. Now, the energy has to be minimized to get the accurate segmented image. This method is robust to initialization, and also eliminates the noise and improves the image contrast. Figure 8 shows the segmentation result of a slice by the method proposed in [13].

Figure 5. Block diagram representing the process of proposed method

Figure 6. Samples for the iterative process of local energy function

Figure 7. Bias corrected image

Figure 8. Segmented image of cardiac left ventricle

4. Results and Discussion
In general, the efficiency of an algorithm is quantified in terms of the deviation of an automated
segmentation with respect to the ground truth. This deviation usually measured from the variations in the intersection or the perpendicular distance between the segmented region with ROI. These deviations can be calculated with some parameters such as DICE, Jaccard, APD, etc.

| Segmentation Method               | Minimum value | Maximum value | Range | Less than 0.7 | Between 0.7 & 1 | Between 1 & 1.5 | Between 1.5 & 2 | Greater than 2 |
|-----------------------------------|---------------|---------------|-------|---------------|----------------|----------------|----------------|----------------|
| Active contour [12]               | 0.5132        | 6.4737        | 5.960 4 | 3             | 14             | 20             | 5              | 8              |
| Level set[7]                      | 0.4432        | 5.4333        | 4.990 1 | 13            | 19             | 9              | 6              | 3              |
| AC with local region fitting [14] | 0.5132        | 6.4737        | 5.960 4 | 3             | 14             | 20             | 5              | 8              |
| Local pre-fitting energy [13]     | 0.5304        | 2.7363        | 2.205 9 | 5             | 15             | 20             | 6              | 4              |
| Proposed                          | 0.4164        | 1.7864        | 1.369 9 | 18            | 17             | 10             | 5              | 0              |

In our proposed method we have considered two such parameters, they are APD and DICE metrics. APD gives the Average perpendicular distance between the automated segmentation and ground truth whereas, the DICE coefficient gives the percent of similarity between both. And thus, for an efficient method of segmentation, the output APD value should be minimum, for instance figure 9, figure 10, i.e. less than 1 whereas DICE value should be the maximum which is approximately equal to 1.

**TABLE 1. OBSERVATIONS - APD METRIC**

The observations are taken from the above-proposed method and tabulated with related other existing methods. By comparing the results obtained of both the existing and the proposed method, precise analysis is made to verify the accuracy of the proposed model. The tabulation is done for the performance evaluation metrics as shown. From the above Table 1, we can observe that the proposed model possesses the minimum APD value when compared to other existing models. The range of the APD metric falls in very minimum value and the probability of images with APD less than one is more in the proposed method i.e. nearly 35 outcomes per 50.

**TABLE 2 OBSERVATIONS – DICE CO-EFFICIENT**

| Segmentation Method               | Minimum value | Maximum value | range | Between 0.7 & 0.8 | Between 0.8 & 0.9 | Between 0.9 & 1 |
|-----------------------------------|---------------|---------------|-------|-------------------|-------------------|-----------------|
| Active contour [12]               | 0.7648        | 0.9768        | 0.2119 | 1                 | 5                 | 44              |
| Level set[7]                      | 0.8107        | 0.9869        | 0.1761 | 0                 | 3                 | 47              |
| AC with local region fitting [14] | 0.7586        | 0.9828        | 0.2241 | 2                 | 2                 | 46              |
| Local pre-fitting energy [13]     | 0.8719        | 0.9814        | 0.1094 | 0                 | 4                 | 46              |
| Proposed                          | 0.9102        | 0.9834        | 1.3699 | 0                 | 0                 | 50              |

Table 2. We can notice maximum value Dice co-efficient in the minimum value column. Since
for an efficient algorithm Dice co-efficient should be high and thus, the proposed method favors algorithm to be more accurate than the existing models. Range i.e. the difference from the minimum to maximum values of the Dice co-efficient is maximum as noted.

### TABLE 3 OBSERVATIONS – EXECUTION TIME

| Segmentation Method                                      | Time (Second) |
|----------------------------------------------------------|---------------|
| Active contour [12]                                       | 45.91         |
| Level set [7]                                             | 48.03         |
| AC with local region fitting [14]                        | 28.69         |
| Local pre-fitting energy [13]                            | 96.66         |
| proposed                                                 | 53.06         |

Table 3 shows the time taken by the segmentation methods to run the method produce the output. On average, the proposed method has a time elapsed of 53.0691372 seconds to run its algorithm. Though it is not the minimum time to say, it is standard to give more accurate results.

![Figure 9. Minimum APD and maximum Dice](image)

![Figure 10. Maximum APD and minimum Dice](image)

The data set used for the experiments are taken from [18] and the experiments were conducted in a system with MATLAB Version 9.5 (R2018b), and configuration of Windows 10 and 12 GB ram.

5. **Conclusion**

Though there are many active contour model with the specific the application to image segmentation, for both general and medical images, all are having a common limitation that is the initial value considered in each method that need to be adjusted to approximate the ground
truth. Most of the active contour method with energy minimization approach solves the common challenges in segmentation such as intensity in-homogeneity and initial level set. This paper takes the advantages of recent active contour with energy minimization model and unifies in a proper way to achieve accurate segmentation at the same time avoids fine tuning the initial values of each methods to every slice to approximate segmentation result to the ground truth. The efficient of the work was given in three tables. Table 1,2 and 3. Lesser the average perpendicular distance closer segmentation result to the ground truth. The proposed unified method segments the left ventricle accurately to a greater number of slices when compared with any other recent methods. We tested each method with 50 cardiac MRI slices. The execution time of proposed method is also comparatively good. This paper investigated a segmentation method that can provide more accurate results than the related existing method. Therefore, using this method, the challenges of intensity in-homogeneity and setting an initial contour is resolved to a greater extent. This work can further be improved by having a proper weight while unifying the recent methods.

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