A Review on Various Image Segmentation Techniques with the applications to Left Ventricle Segmentation in Cardiac MRI

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Abstract- In recent years, Cardiovascular Diseases (CVD) are the prime cause of death. There are many conventional methods for early detection as well as identify the level of severity of the disease. The technology-based on image processing plays a major role in the detection of severances of the disease. Cardiac MRI, one of the preferred medical imaging modalities, is useful for acquiring the anatomical data of heart for clinical diagnosis of cardiovascular diseases. In cardiac MRI, the important parameters for diagnosis are estimated from the Left Ventricle (LV) Segmentation like ejection fraction, LV myocardium mass, stroke volume, etc. Hence segmenting the LV automatically plays a primary and essential role in helping the physician to evaluate cardiac functions quickly since manual segmentation is a time-consuming work. This Automatic Segmentation also eliminates manual errors during evaluation. Different approaches are used for cardiac segmentation. Therefore, the aim of this paper is to review different kinds of segmentation techniques that are being used and to compare those techniques using a parameter that is commonly used in many of the work. Finally presents the most efficient method among the compared methods using parameters like Dice and APD. This paper list the challenges in segmentation that will be helpful for the researchers of the same field to develop and present their idea to solve the segmentation problem.

Keywords – LV Segmentation, DICE, Average Perpendicular Distance

I. Introduction

Cardiovascular diseases are leading causes of death. As per the statistics of WHO [1], it has been projected that about 17.9 million people are accounted to death from CVD's. An explicit analysis of CVD's is required to scale back the death rate. There are many such follow-up cardiac image modalities [2] such as Magnetic Resonance Imaging that provides comprehensive cardiac assessment and the functions of myocardium, computed tomography for brain to extract the cause of stroke and tumors, Single Photon Emission Computed Tomography (SPECT)used to estimate myocardial hypo-perfusion due to coronary stenosis, positron emission tomography (PET),and ultrasound for evaluation of contractile cardiac function[3]. Among all the developed modalities, MRI is widely used approach, since it provides high resolution visualization of cardiac chamber volumes, functions, and myocardial mass. Cardiac MRI has been established as the research gold standard with increased clinical impact. MRI also provides precise information on diagnosis of heart chambers, tissue viability, muscle contraction etc. using adequate techniques.

The cardiac contraction and movement can be quantified by the masses, volumes, and ejection fraction of ventricle. This can be achieved by segmenting the cardiac chambers from the MR images. LV has the most vital role than RV in pumping blood to heart and provides adequate information to analyze the function of heart. Also, RV is six folds thinner than LV and has complex crescent shape which complicates the segmentation process. In digital image processing, image segmentation is an explicit technique helps to partition an image into multiple regions or parts. The segmentation is based on the characteristics of the pixels, which involves separation fore ground from background or clustering regions of pixels based on similarities some characteristics and properties such as color, intensity, texture.

To achieve better amount and quality of imaging data, a variety of segmentation techniques and algorithms have been developed. However, cardiac image segmentation remained a challenge due to the highly dynamic nature of cardiac anatomy, function, and pathology.

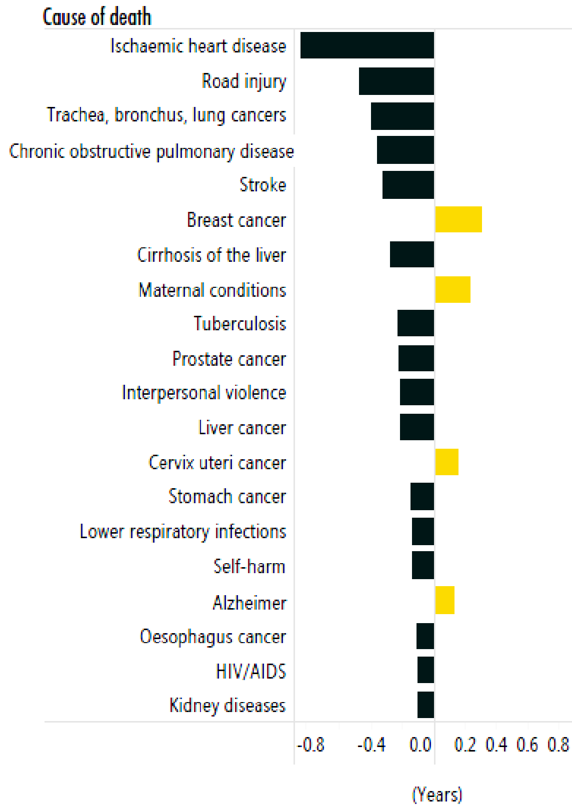

Figure 1. WHO statistics on causes of death in 2019 survey

The following are the different segmentation techniques[4]: 1.Thresholding,2.Clustering methods, 3. Compression based methods, 4. Histogram based methods, 5. Edge detection, 6.Region growing methods, 7. Split and merge methods, 8. Partial differential equation based methods and many more[4]. By using different segmentation approaches, some of the metrics such as dice, mean contour distance, left ventricle (LV) end-diastolic volume (LVEDV) and end-systolic volume (LVESV), LV mass; right ventricle end-systolic volume (RVESV) and right ventricle end-diastolic volume (RVEDV).

II. Overview of Different Methods

In this section, we review various techniques for the segmentation of heart chambers or the whole heart. Cardiac segmentation techniques can be categorised to four main categories: (1) boundary driven techniques, (2) region growing based techniques, (3) graph-cut techniques, and (4) model fitting techniques. We discuss the methods in each category and evaluate the pros and cons [1].

Region-Based Techniques –

In region-based techniques, initially ROI (region of interest) is selected using some model and is partitioned and the information is defined within the ROI to enhance the segmentation performance. Clustering involves in grouping the image pixels of similar features in the image ROI, that in turn provides a segmentation of the image. Clustering techniques include K-means, fuzzy C-means etc.

3.1. K-means Clustering –

K-means clustering works in a progression of steps. They are pre-processing of MRI image, estimation of LV information such as seed points, and the statistical values of region, mapping (polar mapping in general) is generated based on the shape of ROI, correction of segmentation errors if any, segmentation of LV using inverse mapping (inverse polar mapping) [5]. This approach uses an objective function to estimate the performance of a representation for k given clusters and it is defined as

$$\phi(cluster, data) = \left\{\sum_{j\epsilon i} (x_j - m_i)^T (x_j - m_i)\right\} \quad (1)$$

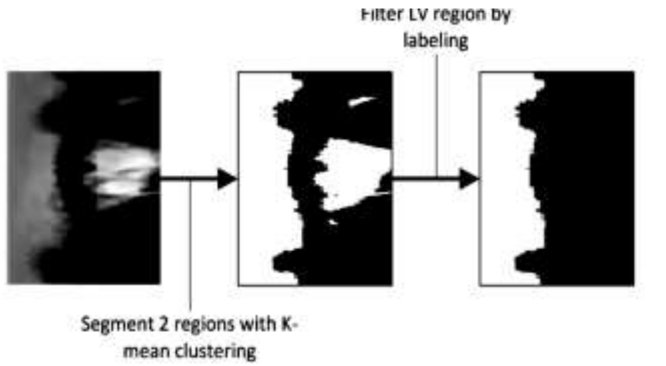

Figure 2. shows the process segmentation by K-means clustering

3.2. Fuzzy C-means –

Fuzzy C-means clustering method has been availed in various fields such as pattern recognition and image segmentation[6].The Fuzzy C-means segments the image into different clusters by grouping the similar gray level into a cluster. The clustering method is computed by minimizing the weight function based on distance between cluster centre and pixels.

Fuzzy clusters results in-constrained soft partition by extending the objective function of hard means[7]. The objective function is expressed as

$$J(p, c) = \sum_{i=1}^{n} \sum_{j=1}^{c} \omega_{ij}^{m} \left||x_i - c_j|\right|^2 \quad (2)$$

Where j defines objective function, p is fuzzy partition of data set, c is centre of the cluster, c_j is the centre of the cluster respectively, n is the number of clusters, x_i represents the feature data of the image such as Gray level and ω_{ij} is the membership of the pixel X_i in the j^{th} cluster.

Few important points to be considered are:[8]

1.It guarantees converge if weight m>1.

2. It finds local minimum of the objective function J_m that minimises the algorithm.

Figure 3. Shows the segmentation of LV using fuzzy C-means

3.3. Level-set based Technique –

In the level set frame-work, the contour automatically splits into several different regions, among which the ventricles are identified because they are the two largest connected components[9]. Remaining components inside the cavities (if any) are removed. The LV and RV are labelled based on the position of their centre of gravity (the RV is to the left of the LV). The different steps of our method are illustrated in the Figure

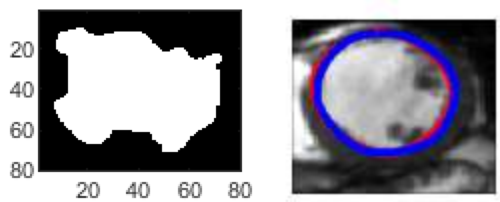

Figure 4. Shows the segmentation of LV using level set method

3.4. Thresholding –

Thresholding is a segmentation technique used to locate the Region Of Interest (ROI) in the LV such as blood pool or myocardium, depending upon the analysis of intensity histogram [10]. Then this intensity histogram is formed as a distribution of pixel intensities. The histogram is divided into sub-intervals depending upon the threshold value which consists of distinctive modes that represents specific intensity. Pixels having intensities in a small interval represents a certain type of tissue. If there is a significant; intensity diversity between the target and the background areas, then is method is effective.

The intensity of different type of tissue may overlap in some cases. Therefore, thresholding is used as a pre-processing step and it may also be combined with other segmentation techniques[11]. Apart from this, it eliminates noise and for further processing the data is prepared to obtain the features. The muscular tissues are the noise which should be removed. Some noise may exist in the form of bones which is catered in the feature selection part. Thresholding is carried out by fixing the value to 85% of the maximum brightness level. From the vigorous experimentation of various data sets, this value is obtained. A good trade-off between accuracy and effort for feature extraction is obtained from this value. Other thresholding technique such as adaptive thresholding does not perform well in this case.

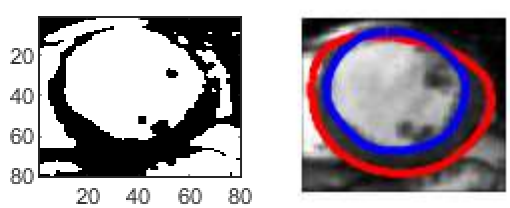

Figure 5. Shows the segmentation of LV using thresholding.

3.5. Adaptive thresholding-

As mentioned above, in thresholding all the pixels are setup by the intensity values above a threshold value as foreground and below threshold value as background i.e. fixed threshold value throughout the process whereas in adaptive thresholding the value is set dynamically which benefits from other thresholding techniques[3]. The dynamically set threshold depends on the intensities of neighboring pixels. To calculate the threshold value $T(X,Y)$ at the pixel positioned at (X,Y) following steps are performed: (i) NxN region is selected around the pixel location. (ii) Calculate the average weight of that region. The average weight $\mathrm{WA}(X,Y)$ can be computed by using either average mean of all pixel location that exist in the region or by Gaussian weighted average of the pixel values. (iii) Find the threshold value $T(X,Y)$ for each pixel. For the single or combination of Gaussian models, the threshold value would be fixed multiples of its variance, where the spatial factors are ignored and only temporal factors are considered[12].

$$T_{adapt} = \frac{k_1\left(\sigma_{curr}^2 + k_2\sigma_{diff}^2\right)}{\mu_{diff}} \tag{3}$$

Where μ_{diff} is the and local mean, σ^2_{curr} is the local variance, σ^2_{diff} local variance.
The limitation of fixed thresholding, that is, the misclassification of foreground pixels with small color differences has overcome by adaptive or local thresholding.

3.6. Otsu's method-

In general, automatic segmentation is a troublesome task in digital image processing. otsu's thresholding uses gray-level histogram of an image, information of each pixel and its spatial correlation information in the neighborhood[13]. This algorithm produces a single intensity value that act as threshold which separate pixels into two classes foreground and background. otsu's thresholding chooses the threshold that minimizes the weighted within-class variance or intra-class variance that in turn maximizes between class variance[14]. The function that gives the intra-class variance is described as

$$t = \omega_1(t)\sigma_1^2 t + \omega_2(t)\sigma_2^2 t \tag{4}$$

The algorithm works as follows:

1. Find the histogram and compute the probabilities for each intensity level.
2. Setup initial class probabilities (ω_i) and class means (μ_i).
3. Repeat the steps for all thresholds t=1,2……up to maximum intensity.
4. From obtained results, update $\omega_i$and μ_i and compute $\sigma_b^2(t)$.
5. Desired threshold corresponds to the maximum $\sigma_b^2(t)$.
6. Calculate the two maxima and their corresponding threshold values.
7. Using the mean value of those two threshold values, desired threshold value is obtained.

The performance of this method for segmentation obtained from the computed results have the following limitations such as small mean variation between foreground and background pixels, small size, large variance of pixels, round pixels, large variance of pixels, large amount of noise etc.

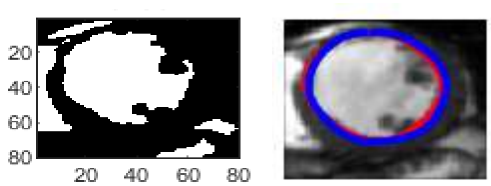

Figure 6. Segmentation LV using Otsu's threshold method

3.7. Active contour without Edges-

The traditional snakes and active contour models depend on the edge function and the image gradient for stopping the curve evolution. But this model forms the curve that is not defined by the gradient. It generates a curve to detect the object on the image that follows the constraints of that image. The initial curve can be wherever in the image, while the interior contours are detected automatically[15]. At first, the curve is detected around the object. After that the curve proceeds towards its interior normal and finds the boundary of the object and stops at the boundary.

Let the evolving curve be C in Ω as the boundary of open subset w of Ω (i.e. $w \subset \Omega$, and $c = \partial\omega$)

$$F_1(C) + F_2(C) = \int_{in(C)} \left|u_0(x,y) - C_1\right|^2 dxdy + \int_{out(C)} \left|u_0(x,y) - C_2\right|^2 dxdy \tag{5}$$

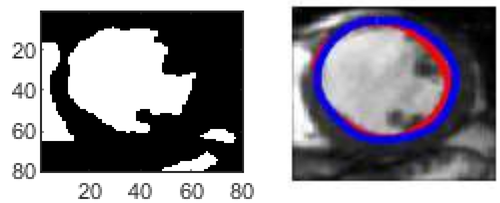

Figure 7. Shows the segmentation of LV using active contour without edges

3.8. Deep learning-

Traditional machine learning techniques needs few prior knowledge and feature engineering for acquiring good accuracy. In Deep Learning it finds the features automatically from the data for detecting objects and segmenting From the given data it learns the features using the learning procedures and in sideways fashion. That's why Deep learning is feasible to apply for image analysis and segmentation[16].

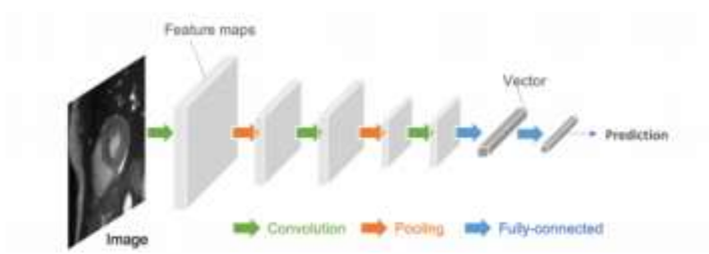

Fig 8. Layers of segmentation process in deep learning

Deep artificial neural network comes under deep learning models. Neural networks include three layers such as input, output and several hidden layers. In convolutional neural network, cardiac MRI are given as input and the hierarchical features from a heap of convolution and pooling operations[17]. These spatial feature maps are flattened and then reduced into a vector over fully connected layers. The forms of vectors may vary based on specific task which can be a predicted label for centre pixel of the input image or co-ordinates of bounding box or probabilities for the set of class.

3.9. Minimum cross entropy-

This method reduces the cross entropy among images i.e. between segmented image and the original un-segmented image. Between the two images the cross entropy is originated in an exceedingly pixel-to-pixel basis and a computationally smart algorithm is developed[18]. In the minimum error approach, the sets of pixels which comprise the object and the background are both assumed to be normally distributed. A criterion function is constructed such that the selected threshold will minimize the average error in pixel classification.

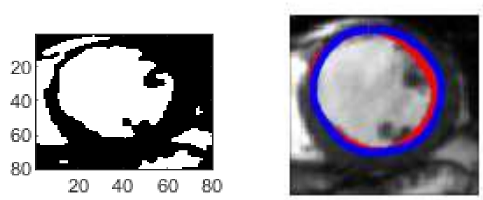

Figure 9. Segmentation LV using minimum cross entropy

3.10. Random forest-

Random forest algorithm has two stages .At first, the region of interest (ROI) is identified and then the LV blood pool ,myocardium and background in the ROI is differentiated .In the beginning the input image given is over segmented into super pixels and using random forest (RF) classifiers each super pixels are classified .The super pixels which contains the parts of LV constitutes the ROI. The output of second set of RF classifiers probability maps for all the ROI pixel that belongs to myocardium, blood poo or background[19]. Then, the integration is applied for probability maps, it is integrated into a second order Markov random field (MRF) cost function and the graph cut optimization is used to attain the final labels.

RF classifiers are used for the following features:

1. The extraction of semantic information are allowed after the training step in the form of relative significance of various features which is important for LV segmentation.

2. For designing an appropriate cost function for segmentation, the probabilistic interpretation of the classification of test samples are allowed in RF classifiers.

3. The RF classifiers discard irrelevant regions for diagnosis away from the LV.

Challenges evoked in segmentation of cardiac MRI-

The challenges faced by various segmentation methods in cardiac MRI are: (i) fuzziness of the cavity borders because to blood flow, acquisition artefacts, and partial volume effect especially for apical slices,[20] (ii) the papillary muscles in the LV pool and wall irregularities, which have the same grey level as the surrounding myocardium and it has not been not be taken into account during segmentation. The epicardial wall which is at the frontier between the myocardium and surrounding tissues has different intensity and it shows poor contrast with the myocardium. This makes segmentation of the epicardial wall difficult.

The LV cavity is surrounded by endocardium[4] MRI is the one which provides fine contrast between myocardium and the blood flow without the need of contrast medium. Due to the papillary muscles and wall irregularities in the heart chambers, which have the same intensity as the myocardium and owing to the gray level in-homogeneities in the blood flow, the segmentation difficulties exists.[21] The development of automated segmentation algorithms has been problematic as a result of the lack of “ground truth” in real clinical cases.

III. Experiment and Result

The computation two metrics namely APD and DICE using various segmentation techniques is performed. APD and dice are the two measures used to find the similarities or differences between the ground truth and the segmented image, where APD gives the Average perpendicular distance of the successful contours. A raw image with ground truth plane is given as input. Results and analysis of metrics using sixteen different segmentation techniques are shown in the table below.

Table -1 Experiment Result

S. No	Segmentation Method	APD	DICE
1.	SD threshold	0.9380	0.9373
2.	Adaptive thresholding	0.8611	0.8562
3.	Active Contour without edges	0.8844	0.8887
4.	Region based Active contour	0.7927	0.8091
5.	GM	0.8655	0.8689
6.	Local Thresholding	0.7256	0.7288
7.	Level Set	0.9034	0.9047
8.	Cross Entropy	0.9312	0.9301
9.	Fuzzy Entropy	0.9251	0.9252
10.	ISO	0.9322	0.9302
11.	Maximum Entropy	0.9291	0.9289
12.	OTSU Thresholding	0.9073	0.8766
13.	EM	0.9200	0.9126
14.	K-Means clustering	0.8776	0.9209
15.	Soft thresholding	0.7513	0.9077
16.	Fuzzy C-means	0.7513	0.7568

IV.CONCLUSION

In this paper, a brief study of different segmentation techniques has presented. The objective function, pros and drawbacks of those methods is analyzed. By using two evaluation metrics that are, DICE and APD, a fine comparison is done between sixteen segmentation methods to guesstimate the performance. From the obtained results, we corroborate some of the efficient techniques such as local threshold, fuzzy C-means method, region based active contours, adaptive threshold and follows. Though the perpendicular distance between the contours been computed, the extended database to find the mean perpendicular distance between the slices and to find the base of the heart seems difficult. Further research is required to pacify the advances in the medical imaging and also to extend these technologies to segment all chambers as well.

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