Date: December 17, 2020, date of current version December 16, 2020.

*Digital Object Identifier xxxx*

# Automatic segmentation of the left ventricle endocardium on each diastolic and systolic images from short axis cardiac magnetic resonance images

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**ABSTRACT** Diagnosing heart diseases from imaging techniques is one of many challenges faced by cardiologists.Segmentation of the left ventricle from Cardiac Magnetic Resonance Imaging (CMR) images is a critical step in this process. In this report, we study and implement an automatic and unsupervised segmentation technique for the left ventricle endocardium to achieve fast and reliable performance in clinical biomedical applications based on the work of Yang et al. This article presents a fully automated left ventricular segmentation in short-axis magnetic resonance imaging. Segmentation was made possible by the use of two clustering-based algorithms; a standard Fuzzy C-Means (FCM) and Circular Shape-constrained FCM (CS-FCM). The algorithm along with the mentioned clustering techniques has been shown to be capable of left ventricle segmentation in the systolic and diastolic phases of the heartbeat cycle. We have been able to reproduce said algorithm on image data obtained from "Automatic Cardiac Diagnosis Challenge" (ACDC) data-set. Furthermore, we have also been able to improve the LV detection by means of incorporating a hyper-parameter tuning operation.Comparisons of our results with ground truth data yielded a 0.89 Dice similarity suggesting the method is able to effectively segment, in most cases, the LV-region both in diastole and systole cycles.

**INDEX TERMS** Left Ventricle, Cardiac Image Segmentation, Magnetic Resonance Imaging (MRI), Medical Imaging

## I. INTRODUCTION

Cardiovascular diseases are a leading cause of death worldwide. Contrary to the advancement in modern medicine, a tendency of increment in the number of cardiac disease cases continue to be observed. People who suffer from or are at a risk of contracting heart diseases need early diagnosis . Thus, there is an active need for a quick and accurate diagnosis of cardiovascular diseases. Diagnosing heart diseases from imaging techniques is one of many challenges faced by cardiologists. Magnetic resonance images (MRI) is the most common method to detect heart diseases. The method of cardiac magnetic resonance imaging (CMR) has established itself as the reference standard for the study of left ventricular function and muscle mass. For this, the results of analysis of the dynamics of the left ventricle (LV) are often used, according to the values of which, it is possible to assess the state of the patient's heart muscle.

Segmentation of the left ventricle within CMR images is an important step in calculating clinical parameters such as ventricular volume and ejection fraction. [2] The task of segmentation of the left ventricle is often encountered in many applications, associated with the analysis of anatomical structures. Therefore, the development of algorithms that automate the procedure for finding the LV contour in images and thereby increase the speed of cardiac image processing and their accuracy is a topic of current interests.For the last few years, many algorithms and methods have been developed and proposed for segmentation of the left ventricle. These methods can be briefly divided into deep-learning and non-deep learning approaches.Most deep-learning approaches use 2D convolutional neural networks and analyze the MRI data slice by slice. Most non-deep learning approaches use image-based techniques like pixel classification methods (clustering, Gaussian mixture model fitting), deformable models (active contour, level-set) and graph-based approaches (graph-cut). But even now, such segmentation is often performed manually as automatic methods for this task have various disadvantages for everyday clinical use, namely, they often require additional calculations and are potentially unstable for patients with pathologies, a series of images are also required, or a complex shape of the segmented area is necessary for consideration. Furthermore, each segmentation algorithm faces some difficulties due to the peculiarities of the anatomical structures. Thus, there is a great need for a fully automated, reliable and fast segmentation method.

In this article, we have tried to reproduce a complete segmentation methodology with automatic segmented area detection as proposed by Yang et al. and have made an attempt to improve upon it. The proposed methodology is a general, non-deep learning based approach and can be easily extended to other biomedical applications in different fields by integrating characteristics into the fuzzy clustering procedure. In the next section, we will take a closer look at the applied segmentation methodology and algorithm, namely standard FCM (Fuzzy C-Means) and CS-FCM (a circular shape-constrained FCM).

## II. METHOD OVERVIEW

In this section, we would like to explain the overall algorithm of the tool. The data-set we have used in order to reproduce the algorithm in the mentioned paper is an MRI dataset published by the "Automatic Cardiac Diagnosis Challenge" (ACDC) organized by an international MICCAI challenge in 2017.[1] The dataset contains 100 cases, divided into 5 batches with 20 normal, 20 myocardial infarction, 20 dilated cardiomyopathy, 20 hypertrophic cardiomyopathy and 20 abnormal right ventricle cases. All the data are Neuroimaging Informatics Technology Initiative (NIFTI) format for anatomized research and training. The case of every patient incorporates general 4D image representation, end-diastolic (ED) and end-systolic (ES) frames with ground truth label images respectively. The input data for the proposed method to perform segmentation consists of 2D short-axis CMR images for both the diastole and systole phases.

The proposed structure of algorithm includes three main stages: First, an auto initialization of the Region Of Interest (ROI) is performed in the first frame of the image. Here, the image is grouped into different regions using the standard FCM algorithm, and the choice of the LV cavity depends on four major characteristics; Intensity, Size, Roundness and Location in the image. The region of interest is then set as a rectangle that is much larger than the anatomically indicated region of the LV. In the second step, LV segmentation is performed within the region of interest using the shape-constrained clustering method. For the purpose of more accurate LV segmentation, we use the circular shape as a constraint, as it is most similar to the shape of the LV cavity in the short axis image. The second step is the start of the CS-FCM algorithm. Thus, pixels that are located in different regions of the image, but have similar intensities, can be distinguished during clustering. In the third step, the rectangle containing the segmented LV cavity is extended to the adjacent image frame and used as the ROI. The first and second steps are performed until LV segmentation is performed on all of the image frames. The approach allows segmenting only the endocardial boundaries of the LV cavity.

### A. AUTOMATIC INITIALIZATION OF ROI

The whole image is clustered into 2 different clusters using a standard FCM algorithm. The ROI is then narrowed down according to four different parameters; Intensity, Size, Circularity and Location. The standard FCM algorithm clusters pixels into two clusters with high intensity and low intensity. Using size, we filter out objects that are smaller than the required value. With the help of circularity, we filter objects whose circularity is less than the necessary value. Location is used to identify objects that are farther from the image boundaries and we ignore objects that are close to the image boundaries. Finally, the bounding box of the selected LV region, and the ROI was specified as a rectangle.

Intensity : The standard FCM algorithm with a cluster number of 2 was employed to segment the image into two clusters with high and low intensities.
Area : A threshold value called "Area_Tol" is used to filter out the objects whose size is smaller than this value.
Circularity : A threshold value called "Round_Tol" is used to filter out the objects whose roundness is smaller than this value.
Location : A threshold value called "Dist_Tol" is used to filter out the objects whose distance to image border is smaller than this value.

Figure 1 provides a complete overview of the processes performed in order to obtain the result. The initial values for the parameters have been listed below:

| Parameter | Cluster number c | Weighting parameter α | Area_Tol | Round_Tol | Dist_Tol |
|---|---|---|---|---|---|
| Value | 2 | 0.3[a] | 374 $mm^2$ | 0.5 | 27mm |

Table 1: Parameter values proposed by Yang et al. (Empirically determined values)

### B. FCM ALGORITHM

The Fuzzy c-means (FCM) is a class of algorithm to perform cluster analysis by partitioning a set of elements into sets of fuzzy clusters. FCM is based on the idea of finding cluster centres by repeatedly adjusting their positions and evaluation of an objective function. It allows more flexibility by introducing the possibility of partial memberships to clusters.[3] It is based on minimization of the following objective function $\mathrm{J}_{fcm}$ with respect to the membership function $\mathrm{u}_{k|ij}$ and the cluster centre $\mathrm{v}_k$,

$$J_{\mathrm{fcm}} = \sum_{x_j \in I} \sum_{k=1}^{K} \left(u_{k|\bar{j}}\right)^m \cdot d_{kij} \quad \text{subj to} \sum_{k=1}^{K} u_{k|jj} = 1, \quad \forall x_{ij} \in I \tag{1}$$

where $m$ is the weighting exponent on fuzzy memberships, and a value of $m = 2$ is known to give good results with the FCM algorithm. $u_{k|j}$ is the membership of the $(i, j)th$ pixel $x_{ij}$ in the $(k)th$ cluster, and $d_{kij}$ is the squared Euclidean distance between the pixel $x_{ij}$ and the cluster centre $v_k$, i.e.

$$d_{kij} = \|x_{ij} - v_k\|^2 \tag{2}$$

The minimization of (1) gives the updating equations for the membership $u_{klij}$ and cluster centre $v_k$ by

$$u_{k|ij} = \frac{(d_{kij})^{-1/(m-1)}}{\sum_{p=1}^{K} (d_{pij})^{-1/(m-1)}} \text{ and } v_k = \frac{\sum_{x_{ij} \in I} u_{k|ij}^m x_{ij}}{\sum_{x_{ij} \in I} u_{k|ij}^m} \tag{3}$$

The steps involved in fuzzy c-means image segmentation are:
Step 1: Initialise the cluster centres and let t = 0.
Step 2: Initialise the fuzzy partition memberships functions ij according to Equation (2).
Step 3: Let t = t + 1 and compute new cluster centres using Equation (3).
Step 4: Repeat Steps 2 to 3 until convergence.

### *C. CS-FCM ALGORITHM*

Circular-shaped (CS) algorithms constrain data points to a circular shape. When this algorithm is incorporated into Fuzzy C-Means it's called CS-FCM.[4] The circular shape function represented by f(i,j,s) is introduced to the standard fuzzy c-means.

$$f(i, j, s) = \left[ \frac{\sqrt{(i - i_c)^2 + (j - j_c)^2}}{r} \right]^{\beta_k} \tag{4}$$

The vector s = $i_c, j_c, r$ represents the circular shape, where $i_c$ and $j_c$ are the x (column) and y (row) coordinates of the centre of circular shape and r is the radius of circular shape; $\beta_k$ is an exponent parameter. In this study, we aim to partition the ROI into two regions; the values of $\beta = 2$ and $\beta = -2$ are set for LV region and non-LV region, respectively. By incorporating the shape distance in (4) into the intensity distance between the pixel $x_{ij}$ and the cluster centre $v_k$ defined by (2), we obtain a new dissimilarity measure $d^{kij}$ such that

$$\hat{d}_{kij} = d_{kij} + \alpha f(i, j, s) \tag{5}$$

where $alpha$ is a parameter to adjust the weight of the intensity-related feature (the first term) against the spatial shape information (the second term). With this dissimilarity measure $d^{kij}$, the pixels with similar intensity but located in different regions can be differentiated. By using the newly defined dissimilarity measure in (5), the objective functional of the proposed CS-FCM algorithm is formulated by minimizing

$$J_{\text{cs}-\text{fcm}} = \sum_{x_{ij} \in I} \sum_{k=1}^{K} \left(u_{k|ij}\right)^m \cdot \hat{d}_{kij} \text{subj to} \sum_{k=1}^{K} u_{k|ij} = 1, \quad \forall x_{ij} \in I \tag{6}$$

The partial derivatives of $J_{\text{cs}-\text{fcm}}$ with respect to the membership $u_{k|j}$ and cluster centre $v_k$ are represented by the following updating equations

$$u_{k|ij} = \frac{\hat{d}_{kij}^{-1/(m-1)}}{\sum_{p=1}^{K} \hat{d}_{pij}^{-1/(m-1)}} \text{ and } v_k = \frac{\sum_{x_{ij} \in I} u_{k|ij}^m x_{ij}}{\sum_{x_{ij} \in I} u_{k|ij}^m} \tag{7}$$

The partial derivative of $J_{\text{cs}-\text{fcm}}$ with respect to $s$ (detailed derivation is given in Appendix) is given by

$$i_c = \frac{\sum_{x_{ij} \in I} i \cdot u_{k|ij}^m}{\sum_{x_{ij} \in I} u_{k|ij}^m} \text{ and } j_c = \frac{\sum_{x_{ij} \in I} j \cdot u_{k|ij}^m}{\sum_{x_{ij} \in I} u_{k|ij}^m} \tag{8}$$

The updated value of the parameter r can be obtained by

$$r = \frac{\sum_{x_{ij} \in LV_B} \sqrt{(i - i_c)^2 + (j - j_c)^2}}{\text{number of } (x_{ij} \in LV_B)} \tag{9}$$

## III. EXPERIMENTAL RESULTS

After the automatic determination of the ROI location using a standard FCM algorithm supplemented with other parameters, the algorithm is able to segment out the LV-region from the ROI. A visualization of the results of the different phases is shown in figure 1. Figure 1 shows the overview of the complete work approach for automatic ROI identification based on the four parameters filtering and then segmentation of the LV region based on CS-FCM :
a) Original CMR image slice from the ADCD dataset.
b) Image clustering based on Intensity with FCM.
c) Boundary detection of each high intensity object.
d) Removing high intensity regions with an area filter.
e) Removing high intensity regions with a circularity filter.
f) Removing high intensity regions with a position filter.
g) Calculation of the bounding box of the selected LV region.
h) Segmentation of the LV-region using CS-FCM algorithm.

The ability of the algorithm to detect the LV region was found to be higher in the middle slices (4-8) and lower in the basal (1-3) and apical (9-11) slices. The algorithm was able to segment the LV region almost all of the middle slices. However, the algorithm fails to detect a ROI in almost 30 percent of the time for the basal and 50 percent of the time for the apical slices.There was no observable differences between the detection of LV-region in the diastolic and systolic phases among the three slice positions.

In figure 2, it can be clearly seen that the middle frames are clearly segmented in both the systole and diastole phases for the patient 001 but the algorithm may fail to detect proper regions for the basal and apical frames.

Comparison of the obtained segmented region was then made with manually segmented contours by expert cardiologists.These ground truth (GT) data are available in the

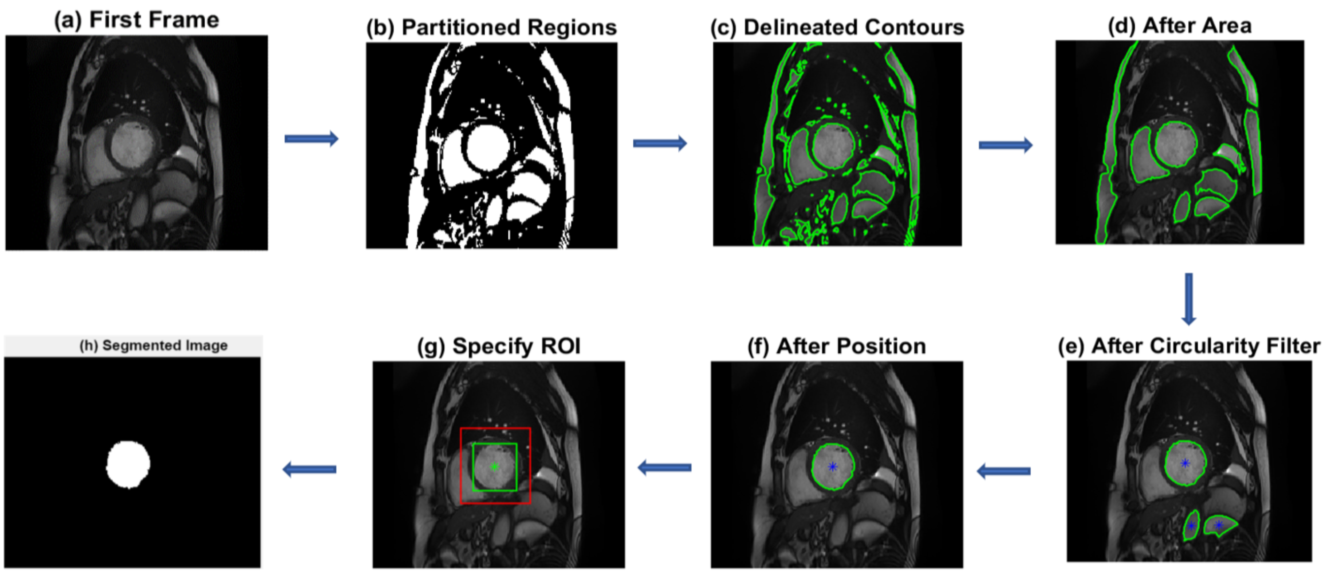


**FIGURE 1.** Demonstration of Automatic LV segmentation (Patient 1 Diastole frame 2)

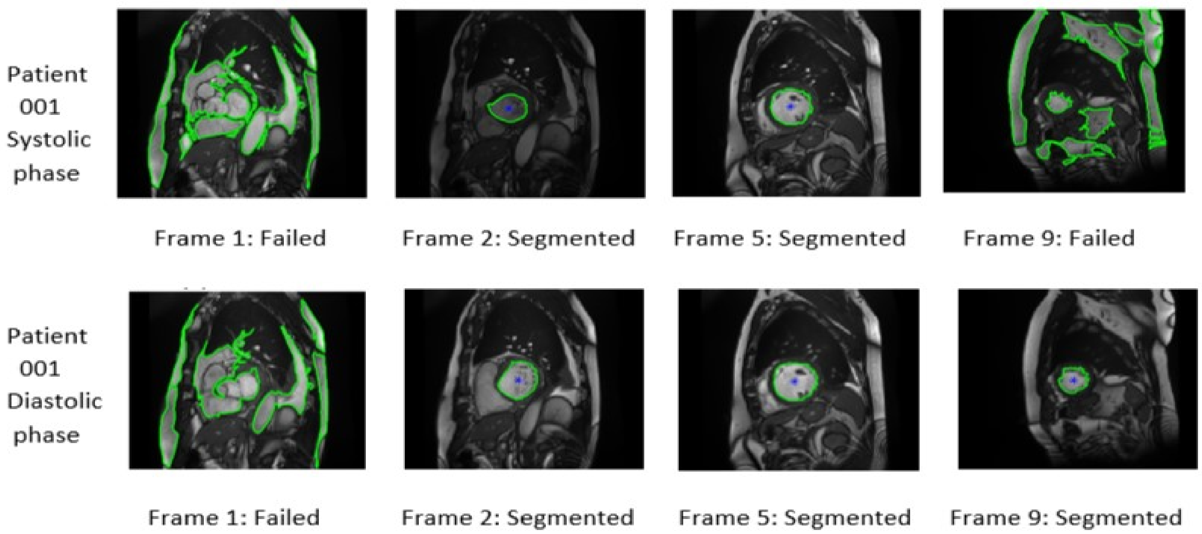


**FIGURE 2.** Segmentation results by frame for Patient 001 for systole and diastole phases

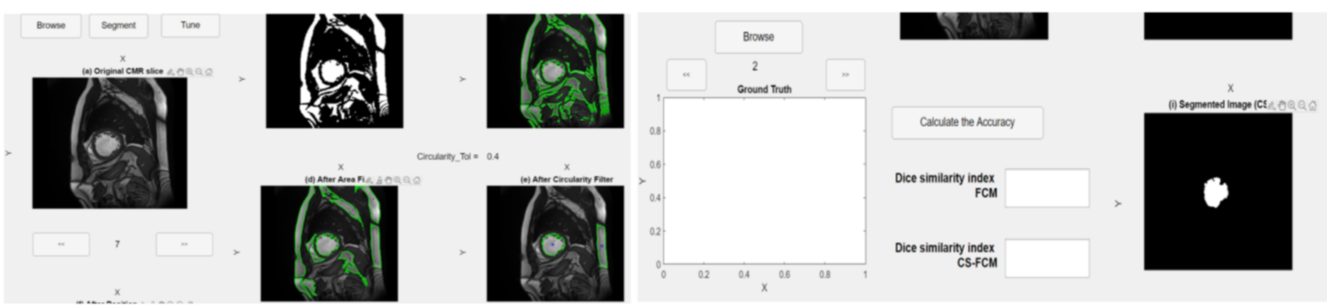


**FIGURE 3.** GUI tool for automatic segmentation

ACDC dataset Challenge [1] website labelled as "gt". Dice similarity was observed in average to be 0.88 without the CS-FCM implemented and 0.89 after the CS-FCM algorithm was implemented.

Figure 3 depicts the MATLAB app tool developed. It is an executable tool that inputs a 2-D NIFTI format CMR images and segments the LV-region automatically. The software is capable of displaying each step of the overall process as separate images. It also allows the user to cycle through the image slices of the selected image and segment them one-by-one. Furthermore, calculation of accuracy using the Dice similarity against ground truth data can also be made within the tool framework.

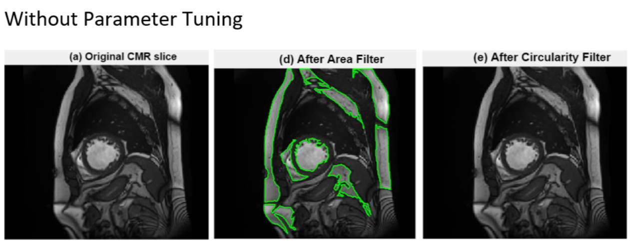


**FIGURE 4.** Algorithm fails to detect the ROI

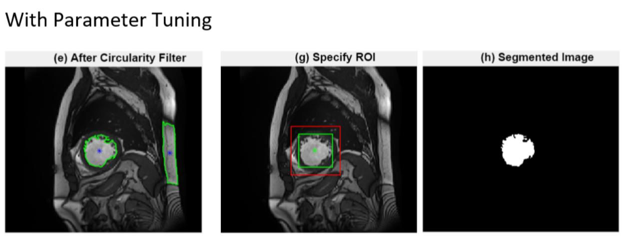


**FIGURE 5.** Algorithm is able to detect the ROI

Figures 4 and 5 showcase the effect of using a hyperparameter tuning operation on the parameters to obtain optimal parameters. Using the proposed method without any hyper-parameter tuning operation in effect, the algorithm fails to segment the image into LV- region from patient 1 slice 7. However, with the introduction of a tuning operation, the algorithm is now able to segment the LV-region accurately.

### *A. ACCURACY DETERMINATION USING DICE SIMILARITY COEFFICIENT*

The Dice similarity coefficient, also known as the Sørensen–Dice index or simply Dice coefficient, is a statistical tool which measures the similarity between two sets of data. This index is the most broadly used tool in the validation of image segmentation algorithms.[5] The Dice similarity index values ranges from 0-1.

Comparisons of the segmented image by the proposed algorithm was made against Ground truth data provided in the ACDC dataset using the Dice similarity index as a measure of accuracy of the result obtained. Both the results, from standard FCM as well as CS-FCM were measured.

### *B. EXECUTABLE GUI-BASED TOOL DEVELOPMENT*

A GUI based tool was then developed using MATLAB apps that allows easy input of NIFTI format images and segments the LV-region based on the proposed algorithm.

### *C. COMPUTATIONAL PERFORMANCE*

The computational time was measured on a ASUS Zenbook 14 laptop (Intel Core i7-8850 m@2.6 GHz) with a MATLAB (version R2020a) implementation. The working approach process includes identifying the ROIs, reading the raw images and saving the extracted contours. LV segmentation per frame is 1.46 s on average.

## IV. DISCUSSIONS

In this project, we were able to reproduce, improve upon the algorithm proposed by Yang et al. for the Automatic detection of Left Ventricle in both, diastole and systole from short-axis cardiac magnetic resonance (CMR) images and create a GUI tool in MATLAB. Using circular shape-constrained fuzzy segmentation method supplemented with parameter-based filtering as mentioned in the paper, we were able to segment the CMR images from the ACDC dataset into well-defined LV-regions.

From figure 1, we can clearly see the auto-segmentation of the Left ventricular region, which are practically acceptable for all frames, regardless of image variations.

From the above images, it evident that the standard FCM failed to separate the LV area from other bright areas. All bright objects, including LV, are separated from each other into one cluster as shown in figure 1(b). As expected, the proposed CS-FCM sharding approach performs much better.From the presented figure and the obtained segmented areas, it can be concluded that this algorithm successfully distinguishes the LV cavity from other light structures, and also correctly segments the LV cavity.

The error in the detection of ROI and its subsequent inability to segment the LV-region was found at all times in the basal and apical slices. For the basal slices, this may be attributed to the aorta and pulmonary artery leaving the ventricles and crossing into each other;s ventricular territory. This resulted in error in location of the bright round structure as the LV cavity. For the apical slices, this error may be attributed to the size of the LV cavity in these frames. In the apical slices, as the size of the LV appears to be very small, the "Area_tol" filter parameter results in filtering out of the ROI and thus, segmentation fails consequently.

The proposed CS-FCM algorithm integrates both intensity related feature and spatial shape information into the clustering procedure. As a result, pixels having similar intensity information but located in different regions (LV region and non-LV region) could be differentiated.

The results showed two obvious advantages of the proposed CS-FCM than standard clustering algorithms like FCM: it successfully distinguishes the LV from other structures which have similar intensity as LV, and it correctly segments the LV even when papillary muscles are adjacent to the LV structure in the image.

The proposed algorithm is fully automatic and unsupervised. One major merit being, purely image driven and, therefore, the algorithm does not require any prior training. Another merit is that the segmentation process is fully automatic and does not require any initialization or user interaction. However, the effectiveness of unsupervised methods can be limited by anatomical or image contrast variability encountered in real-world data.

## V. IMPROVEMENT ON THE PROPOSED METHOD

Certain limitations have been discussed by Yang et. al, one of which includes difficulty in segmentation of LV from the RV in presence of other similar circular structures such as the aorta. To solve the said issue, we have proposed a hyperparameter tuning operation on the given parameters. This has been observed to significantly improve the segmentation of the LV from the RV region. From the figures 4 and 5, we can say that the addition of the a hyperparameter tuning operation has greatly improved the ability of the algorithm to correctly detect and segment the LV-region and thus, can effectively eliminate some of the limitations discussed by Yang et al.

## VI. CONCLUSION

The circular shape-constrained fuzzy segmentation method supplemented with parameter-based filtering algorithm proposed by Yang et al. has demonstrated a simple yet effective means for automatic detection of LV region from short-axis cardiac magnetic resonance (CMR) images. In this report, we have been able to reproduce the entire process, improve upon the proposed method and implement a GUI-based tool for Left-Ventricular segmentation.Comparisons of our results with ground truth data yielded a 0.89 Dice similarity suggesting the method is able to effectively segment, in most cases, the LV-region both in diastole and systole cycles. As discussed in the paper, the proposed tool does not require any kind of initial training or initialization and therefore, could have better and easier real-world applications than other methods based on training.

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