

A Study of Preprocessing and Segmentation Techniques on Cardiac Medical Images

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Abstract - Segmentation is the process of simplifying and/or changing the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries in images. Medical image segmentation plays a crucial role in delineation of regions of interest under study. It is essential in almost any medical imaging applications and is an essential step towards automated disease state detection in diagnostic imaging. Myocardial infraction is the leading cause of death throughout the world. Foreseeing and diagnosing of cardiac diseases usually require quantitative evaluation of the ventricle volume, mass, and ejection fraction. Advantages and disadvantages of the current segmentation methodologies are reviewed in perspective of medical imaging.

Index Terms—Image Segmentation, Left ventricle (LV), Myocardial wall segmentation, Ejection Fraction (EF), wall thickness.

I. INTRODUCTION

The heart is a vital organ of the human circulatory system. Proper functioning of the heart is essential to prevent Cardio Vascular Diseases (CVD). Lack of cardio vascular exercise, sedentary and stressed lifestyle, unhealthy diet, diabetes and genetic factors, all contribute to the development of cardio vascular disorders. Generally, cardiac examination involves assessing a combination of the four following physiological measures: cardiac structure, function, perfusion and myocardial viability. Delineating the myocardial wall of the Left Ventricle (LV) is an important step in the prognosis and diagnosis of cardiac diseases. Analysis of the LV in particular has attracted a lot of attention in the medical imaging community, as numerous CVD symptoms are manifested through variations in the left ventricle's volume, mass or motion pattern. Ejection Fraction (EF) of the left ventricle is another important clinical measure, which is derived based on the LV volume at two critical cardiac phases. While segmentation of the left ventricle in each short-axis slice at any time instance provides volumetric data of the given phase, tracking or detection of the ventricle boundaries through the cardiac cycle represent the ventricle motion. This topic has been investigating for decades [1], and it is still an active research field [2]-[4]. The main challenges include wide shape variability of heart between different cardiac

cycles and between different patients, weak edges between epicardium and heart fat or soft tissues. According to the latest statistics released by European Heart Network, CVDs are the primary cause of all deaths in the European Union. Every year 4.35 million people die from cardio vascular disease in Europe and 2 million in European Union. CVD is also one of the primary causes of disease burden in Europe. Regular examination and monitoring of individuals in the high risk group is essential in keeping down the rate of cardio vascular disease in the society. Traditionally, blood pressure monitoring, blood test for detecting cholesterol and ECG were considered as the only options for monitoring cardio vascular health of an individual. However, with the advancements in medical science and development of new technologies, the examination of an individual with respect to cardio vascular diseases has seen some major changes. Some of the more established techniques include: Ultrasound (US), single-photon emission computer tomography (SPECT), computed tomography (CT), and Magnetic Resonance Imaging (MRI). MRI examination of large number of cardio vascular patients in the society generates a significant volume of data and is considered as a golden standard for cardiac imaging. Additionally, they have the potential to provide valuable clinical information such as cardiac structure and function measurements. However, there are some limitations in widespread use of MRI in clinical applications; the most important of all being the fact that during each cardiac MRI acquisition, more than 100 static 2D scans are generated. In order to evaluate cardiac function measures such as ejection fraction, one has to segment the LV in each of the slices and time frames. Manual segmentation of the LV is very labour-intensive and it is considered to be the bottleneck of the MRI process. Therefore, any application that facilitates semi- or fully automatic segmentation of CMR images will be beneficial to the medical imaging community. Most of the cases, doctors prefer Cardiac CT imaging, it has also been evaluated for assessment of functional parameters of the heart, which have to be interpreted in strong relationship to the cardiac vessels and the presence of stenosis in the vessels. Among these parameters myocardial wall perfusion and viability, wall motion and heart valves.

However, in order to access all these parameters, powerful tools have to be provided to the clinicians. Although these tools are partly existent for MR imaging techniques,

there is a lack of efficient and user-friendly software for MSCT-based cardiac diagnosis. The core of all these applications is the extraction of the LV or Right Ventricle (RV) or Myocardium without time-consuming user interaction. Analysis of these data by radiologists or the doctors is time consuming and suffers from differences in interpersonal assessment due to the absence of standardization techniques in analysis. Therefore, application of computers in image processing and analysis could be one of the possible solutions. The last few decades have seen a rapid advancement in the development of robust techniques in the domain of image processing and pattern recognition. Many of these techniques have been successfully employed to solve problems in the domain of medical science.

The objective of this paper is to make a study on robust segmentation techniques for left ventricular or right ventricular segmentation and/or followed by MyoCardiac wall extraction. Cardiac images consist of huge volumes of data. All the images are not manually post processed. Normally, manual tracing of the contour of the ventricle is done in the systolic and diastolic stage of the heart. Manual tracing of the contour and hence computation of the volume of blood suffers from personal bias, and inter-observer variations. Difference in the volume of ventricular blood in systolic and diastolic stage is used to determine the ejection fraction. With increasing number of people suffering from cardiac diseases manual post-processing is becoming increasingly difficult and time consuming, introducing more errors. Different methods are existing for segmentation of the cardiac image data. In this paper, a review regarding the various cardiac image segmentation methods are included.

II. RELATED WORKS

Automatically detecting the Ventricles and myocardial wall of the left ventricle (LV) is an important step in the prognosis and diagnosis of cardiac diseases. The main challenges include wide shape variability between different cardiac cycles and between different patients, weak edges between epicardium and heart fat or soft tissues, and thin thickness of the RV wall. Model-based methods have become dominant in this research to get an accurate and robust segmentation. Normally, a heart model is built by learning the geometric or intensity features of the heart from cardiac images. While in segmentation, a commonly used framework is first globally aligning the model to an image and then deforming this model to fit image content. Global localization is achieved by detecting the geometric or intensity features of the heart. Local deformations are performed by optimizing an objective function defined between the model parameters and image features. In particular, the model-based methods [5] can be roughly categorized based on whether these models are applied explicitly or implicitly for segmentation. In the first type of methods, typically a heart surface model is fitted to images for segmentation. For example, in active shape models (ASMs), a statistical shape model called the point distribution model is learned from a set of aligned shapes using the principal component analysis (PCA) technique, which is then iteratively aligned to image boundaries. Active appearance models (AAMs) extend this idea by incorporating

gray level information and were used in segmenting the left and right ventricles from images. The deformations allowed in the parametric models such as ASMs and AAMs are restricted to the shape space where the heart models are embedded. Using deformable models, it provided a way to incorporate shape priors that allows adaptivity for local variations. In these methods, an annotated heart surface model is deformed to match image content by optimizing affine or similarity transformations defined between the model parameters and image features. Instead of deforming a pre-aligned model, atlas based methods use shape information implicitly by directly registering atlas image to a target image. Then, either the labels from multiple atlases are fused or registered atlases are deformed to extract the heart chambers. How to localize the model initially is a less studied topic, especially for these methods using deformable models, which tend to get stuck in undesirable local extreme when started without a good initialization. Typically, the geometric features of the heart are used for localization. For example, in many cardiac CT images, it is initialized by searching for a circular structure in a blood pool mask obtained via Thresholding. Examples of more advanced localization methods include the generalized Hough transform and optimization of similarity transformation for a heart model. Atlas-based registration has also been used for coarse initialization. One common feature shared with most of the methods described so far is that they start with some global localization and then capture local details. This strategy works well when global features of a given object are well defined, but may not hold for small structures such as the LA, since the contribution to a cost functional may be overwhelmed by large structures such as the LV or strong artifacts associated with image quality. Instead of starting globally, region growing provides another perspective to the problem that begins locally to capture the entire target. This local property makes it more adaptive to variations of the dataset. In region growing approaches, starting from seed regions, voxel neighboring to a given voxel are merged according to an aggregation criterion. Image intensity homogeneity is a widely used criterion in a growing process. Shape priors can be naturally incorporated into a growing process to segment complex objects. Typically, these priors are defined as some distance between reference and observed shapes. To this end, the reference shape needs to be aligned to the observed shape before computing the shape distance. A more abstract way of defining shape distance employs shape moments, which removes the requirement of aligning shapes for the distance computation. The following section presents a review on selected papers based on various pre-processing steps, and image segmentation techniques in cardiac MRI and CT images. The main objective is to perform a critical appraisal of these techniques.

A. Cardiac Image Pre-processing Techniques

Since most of the real life data is noisy, inconsistent and incomplete, so preprocessing becomes necessary. Image pre-processing is one of the Preliminary steps which are highly required to ensure the high accuracy of the subsequent steps.

The CT and MRI cardiac images normally consist of some artifacts; patient specific and image processing and equipment based artifacts. Patient specific artifacts includes motion beam hardening, metal artifact. Others include partial volume effect, ring and staircase artifacts. So it is needed to be removed by pre-processing procedures before any analyzing. The enhancement activities also used to remove the film artifacts, labels and filtering the images. Several denoising approaches have been surveyed and analyzed in this section.

- i. **Gabor Filters:** These primitive methods along with reducing the noise blur keeps the important and detailed structures necessary for subsequent steps. It is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination.
- ii. **Adaptive Filters:** It is developed for impulsive noise reduction of an image without the degradation of an original image. The image is processed using an adaptive filter.
- iii. **Morphological Operation:** Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Erosion and dialation are the two fundamental operations. Erosion removes small-scale details from a binary image but simultaneously reduces the size of regions of interest. The dilation operation usually uses a structuring element for probing and expanding the shapes contained in the input image. In compound operations, many morphological operations are represented as combinations of erosion, dilation, and simple set-theoretic operations such as the complement of a binary image. Opening is erosion followed by dialation and it is less destructive than erosion. Closing is dialation followed by erosion. Closing is so called because it can fill holes in the regions while keeping the initial region sizes.
- iv. **Mean Filters:** The idea of mean filtering is simply to replace each pixel value in an image with the mean (average) value of its neighbours, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Mean filtering is usually thought of as a convolution filter. Like other convolutions it is based around a kernel, which represents the shape and size of the neighbourhood to be sampled when calculating the mean. Often a 3*3 square kernel is used, although larger kernels (e.g. 5*5 squares) can be used for more severe smoothing. A small kernel can be applied more than once in order to produce a similar but not identical effect as a single pass with a large kernel.
- v. **Image Normalization:** Normalization is a process that changes the range of pixel intensity values. Normalization is sometimes called contrast stretching or histogram stretching. The purpose of dynamic range

expansion in the various applications is usually to bring the image, or other type of signal, into a range that is more familiar or normal to the senses, hence the term normalization. The motivation is to achieve consistency in dynamic range for a set of data.

vi. **Histogram Equalization:** The dilation operation usually uses a structuring element for probing and expanding the shapes contained in the input image. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. The method is useful in images with backgrounds and foregrounds that are both bright or both dark.

vii. **Weighted Median Filter:** It can remove salt and pepper noise from CT images without disturbing of the edges and have the robustness and edge preserving capability of the classical median filter. WM filters have noise attenuation capability. WM filters belong to the broad class of nonlinear filters.

viii. **Wiener Filter:** Wiener filter is a type of linear filter and have been used extensively for the restoration of noisy and blurred image. Wiener filters a gray scale image that has been degraded by constant power additive noise.

ix. **Contrast agent accumulation model:** This improves only the contrast of the image and the unwanted tissues are not eliminated.

B. Cardiac Image Segmentation Techniques

An image in computer vision system could be defined as a two dimensional or three dimensional matrixes of pixels, where each pixel corresponds to a definite intensity value. In medical imaging, these intensities could be radiation absorbed during x-ray, or acoustic pressure in ultrasonography, or radio frequency signals in MRI etc. Image segmentation is a procedure in which an image is divided into regions of some homogeneous characteristics like grey scale value, colour or texture. Cardiac image segmentation methods could be broadly categorized into following:

1. Histogram Based Methods
2. Statistical Model Based Methods
3. Region Based Methods
4. Graph Based Methods
5. Deformable Model Based Methods
6. Atlas Based Methods

Even though it is a broad classification, some methods are combined together to achieve a good segmentation.

- i. **Histogram Based Methods:** They typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Color or intensity can be used as the measure. By

using intensities, certain thresholds are selected. Binary thresholding segments an image into two classes depending on the threshold. All pixels with intensities above the threshold is classified into one group and all pixels with intensities less than the threshold is classified into a second group. Pritee Gupta, Vandana Malik *et al.* proposed [6] a multilevel threshold method. This work aims to presents an adaptable segmentation method and is based on a model of automatic multilevel thresholding and considers techniques of group histogram quantization as pre-processing step. Then analysis of the histogram slope percentage and calculation of maximum entropy to define the threshold for segmentation purpose. The algorithm automatically gets the threshold, by the histogram analysis, finds the histogram valleys, which are the places where are concentrated the thresholds and therefore the subdivision of the image. Method proves effective in cases where the image and the histogram are well defined, and for cases where the image is not presented optimally with noise, distortion and non standardized histograms. Segmentation results entirely depend on the key threshold. A similar method by Mengqiu, Tian *et al.* proposed [7] an automatic K-means initialization algorithm based on histogram analysis, which manages to overcome intrinsic limitation in K-means clustering; the choice of initial clustering centroids. Histogram equalization is the pre-processing step. Once histogram is computed, it detects all local maxima in the histogram. Then, choose the global maximum of the histogram as the first centroid. Then, repeatedly identify the remaining centroids. Jean-Philippe Morin *et al.* [8] proposed histogram based approach for segmentation to cardiac CT or brain MRI images. Filtering and Morphological operations are the pre-processing steps. This method shares similarities with the Mean-shift algorithm, as it finds the modes of the intensity histogram of images. Find peaks by constructing a graph. Then, a random walk probability class constructed based on transition probability matrix results segmented output. By computation, the TPM the complexity becomes $O(N^2)$. The method can only be used for gray level images.

ii. **Statistical Model Based Methods:** In this method, a heart model is built by learning the geometric or intensity features of the heart from cardiac images while in segmentation, globally aligning the model to an image and then deforming this model to fit image content. Two variants are ASMs and AAMs [9]. AAM extends ASM by taking into account image intensity values of the structures and surroundings. AAM has better convergence than ASM but is much slower. One significant disadvantage of these methods is that accurate segmentation of a large training set is required to cover the inter-patient variances in applications. The computational cost is another obstacle for these methods in high dimensional domains. A paper on Left Ventricle segmentation in CT images [10] presented by M.G. Danilouchkine *et al.* make use of line parameterization for preprocessing step. The method described in this paper solves under estimation and overestimation by the

selection of candidate points with Fuzzy Inference to determine update steps for edge detection. A triangular mesh constructed from sample points for model generation. During the matching, this mesh is intersected by the image planes, thus generating contours spanned by the intersections of the mesh triangles. Olivier Ecabert *et al.* proposed an automatic model based segmentation of heart in CT images [11]. Pre-processing steps used are sub-sampling, thresholding, smoothing, Edge Detection by sobel and Pruning. Segmentation process consists of heart localization and model adaptation. Generalized Hough Transform is used for localization. The method gives good results. Main problem with GHT is that it has higher computation cost and memory demand.

iii. **Region Based Methods:** This method attempt to partition or group regions according to common image properties such as intensities, textures, patterns etc. Algorithm proposed by Chao Li, Xiao *et al.* [12] performs a semi-automated segmentation of epicardium and endocardium. In this myocardium thickness is also estimated. Paper does not perform any pre-processing steps. Initialization step is the selection of seed point in LV cavity. To roughly detect LV and thickness, maximum likelihood is used. In other paper [13] proposed by Dominik Fritza *et al.* by starting with a single click in the ascending aorta; the aorta, the left atrium and the left ventricle get segmented with the slice based adaptive region-growing algorithm. Paper shows some drawbacks in the sense that the region growing step failed in some cases due to motion artefacts. Harikrishna Rai, G.N, T.R. Gopalakrishnan Nair in their paper [14] proposed a method for segmenting anatomical structures like aorta. No preprocessing step used in this paper. A homogeneity criteria based on gradients is used for region growing growth. For each pixel, it takes four adjacent neighbours, and stack is used to traverse the neighbourhood pixels around the seed location. If a homogeneity criterion is met, add them to the stack. As long as the stack contains unvisited voxel, a voxel is popped from it and all its neighbours are processed. The seed selection is manual; if selection and homogeneity criteria used are not proper, results will not be correct. A same method to the above said is proposed by Hae-Yeoun Lee, [15] *et al.* and a FIFO queue is used as data structure to store the processed voxel.

iv. **Graph Based Methods:** The graph cut method solves the image segmentation problem by constructing a graph that includes both the boundary and regional information of the image. A cut with minimal cost is then pursued which aims to separate the object nodes of the graph from the background. Seed selection carried out by taking a rough ROI. The main advantage of the algorithm is that it is able to provide a global optimal solution. Another advantage is its flexibility to extend to 3D or even higher applications. Martin Urschler *et al.* [16] in their paper proposed a live-wire approach for segmentation of left ventricle. No preprocessing steps are used in this. Ventricles segmentation is achieved by an intelligent scissors algorithm and Dijkstra's algorithm. At first image under consideration is defined as a graph. Then a

local cost function is assigned to the graph edges to weight their probability of being included in an optimal path. The basic problem of finding a boundary segment is therefore converted to finding a minimum-cost path between start and end vertex of the segment. The main problem of the proposed method is, it make use of an expert radiologist for initial seed point selection.

v. **Deformable Model Based Methods:** These are for delineating region boundaries using 2D closed parametric curves or 3D surfaces which deform under the influence of internal and external forces. External forces can be constructed from a feature space or directly from the image, and it drive the curve or surface towards desired image features like lines and edges. Using deformable models, the authors in [17] provided a way to incorporate shape priors that allows adaptivity for local variations. In these methods, an annotated heart surface model is deformed to match image content by optimizing affine or similarity transformations defined between the model parameters and image features. Many of the segmentation works in cardiac images involves the extraction of LV and RV .One observation that may be utilized for the localization is that the ventricles are salient components on the heart surface. This is where the shape decomposition/segmentation technique can be utilized to cluster the surface into meaningful components based on some given criteria as in computer graphics and geometric modelling [18], [19]. How to localize the model initially is a less studied topic, especially for methods using deformable models, which tend to get stuck in undesirable local extrema when started without a good initialization. Typically, the geometric features of the heart are used for localization. For example, in [20], the LV endocardium was initialized by searching for a circular structure in a blood pool mask obtained via thresholding. A similar empirical rule was used in identifying the left ventricle cavity [21]. Liangjia Zhu *et al.* proposed in their paper [22], a method for myocardial wall extraction using shape segmentation followed by variational region growing. Paper shows better results for the myocardium and ventricle extraction.

vi. **Atlas Based Methods:** In this, an atlas describes different structures present in a given type of image .Given an atlas; an image can be segmented by mapping its coordinate space to that of atlas by registration process. Instead of deforming a prealigned model, atlas-based methods use shape information implicitly by directly registering atlas image to a target image. Then, either the labels from multiple atlases are fused [23] or registered atlases are deformed [24] to extract the heart chambers.

III. CONCLUSION

The result of preprocessing followed by segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image .Each of the pixels in a region are similar with respect to some characteristic or computed property, such as colour, intensity, or texture. Due

to the importance of cardiac image segmentation, a number of algorithms have been proposed .But based on the image that is inputted, the algorithm should be chosen to get the best results. In this paper the various algorithms that are available for cardiac CT and MRI gray scale images are studied.

REFERENCES

- [1] J. S. Suri, "Computer vision, pattern recognition and image processing in left ventricle segmentation: The last 50 years," *Pattern Anal. Appl.*, vol. 3, no. 3, pp. 209–242, 2000.
- [2] C. Petit jean and J. N. Dacher, "A review of segmentation methods in short axis cardiac MR images," *Med. Image Anal.*, vol. 15, no. 2, pp. 169–184, 2011.
- [3] MICCAI Workshop-Cardiac MR Left Ventricle segmentation Challenge, Available : <http://smial.sri.utoronto.ca/LVChallenge/Home.html>
- [4] MICCAI Workshop—3D Cardiovascular Imaging Segmentation Challenge, [Online]. Available: <http://grand-challenge2012.bigr.nl/>
- [5] T. F. Cootes, C. J. Taylor, D. H. Cooper, and J. Graham, "Active shape models-their training and application," *Comput. Vis. Image Understand.*, vol. 61, no. 1, pp. 38–59, 1995.
- [6] Pritee Gupta, Vandana Malik, "Implementation of Multilevel Threshold Method for Digital Images Used In Medical Image Processing", Volume 2, Issue 2, February 2012 ISSN: 2277 128X International Journal of Advanced Research in Computer Science and Software Engineering.
- [7] Mengqiu Tian, Qiao Yang, Andreas Maier, Ingo Schasiepen, Nicole Maass, Matthias Elter, "An automatic histogram-based initializing algorithm for K-means clustering in CT".
- [8] Jean-Philippe Morina, Christian Desrosiers and Luc Duonga, "Image segmentation using random-walks on the histogram".
- [9] O. Ecabert, J. Peters, H. Schramm, C. Lorenz, J. von Berg, M. Walker, M. Vembar, M. E. Olszewski, Subramanyan, G. Lavi, and J. Weese, "Automatic model-based segmentation of the heart in CT images," *IEEE Trans. Med. Imag.*, vol. 27, no. 9, pp. 1189–1201, Sep. 2008.
- [10] H.C. van Assen, M.G. Danilouchkine, F. Behloul, H.J. Lamb, R.J. van der Geest, J.H.C. Reiber, and B.P.F. Lelieveldt, "Cardiac LV Segmentation Using a 3D Active Shape Model Driven by Fuzzy Inference", MICCAI 2003, Lecture Notes in Computer Science, R.E. Ellis and T.M. Peters, Eds., vol. 2878. Berlin: Springer Verlag, 2003: 533-540.
- [11] Olivier Ecabert, Jochen Peters, Hauke Schramm, Cristian Lorenz, Jens von Berg, Matthew J. Walker, Mani Vembar, Mark E. Olszewski, Krishna Subramanyan, Guy Lavi, and Jrgen Weese "Automatic Model-Based Segmentation of the Heart in CT Images", IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 27, NO. 9, SEPTEMBER 2008 1189
- [12] Chao Li, Xiao Jia and Ying Sun, "Improved semi-automatic segmentation of cardiac CT and MR images", 978-1-4244-3932-4/09/2009 IEEE.
- [13] Dominik Fritza, Daniel Rinckb, Roland, Rudiger Dillmanna, Michael Scheueringb, "Automatic Segmentation of the Left Ventricle and Computation of Diagnostic Parameters Using Regiongrowing and a Statistical Model."
- [14] Harikrishna Rai, G.N, T.R.Gopalakrishnan Nair "Gradient Based Seeded Region Growing Method for CT Angiographic Image Segmentation."
- [15] Hae-Yeoun Lee, Noel C. F. Codella, Matthew D. Cham "LV Segmentation using iterative Thresholding and ACM with adaptation on MRI/CT data."

- [16] Martin Urschler, Heinz Mayer, Regine Bolter, Franz Leberl, "The Livewire Approach for the Segmentation of Left Ventricle Electron-Beam CT Images."
- [17] Y. Zheng, A. Barbu, B. Georgescu, M. Scheuering, and D. Comaniciu, "Four-chamber heart modeling and automatic segmentation for 3D cardiac CT volumes using marginal space learning and steerable features," *IEEE Trans. Med. Imag.*, vol. 27, no. 11, pp. 1668–1681, Nov. 2008.
- [18] A. Shamir, "A survey on mesh segmentation techniques," *Comput. Graph. Forum*, vol. 27, no. 6, pp. 1539–1556, 2008.
- [19] M. Attene, S. Katz, M. Mortara, G. Patan`e, M. Spagnuolo, and A. Tal, "Mesh segmentation—A comparative study," in *Proc. IEEE Int. Conf. Shape Model. Appl.*, 2006, pp. 14–25.
- [20] M. Jolly, "Automatic segmentation of the left ventricle in cardiac MR and CT images," *Int. J. Comput. Vis.*, vol. 70, no. 2, pp. 151–163, 2006.
- [21] M. Lynch, O. Ghita, and P. Whelan, "Automatic segmentation of the left ventricle cavity and myocardium in MRI data," *Comput. Biol. Med.*, vol. 36, no. 4, pp. 389–407, Apr. 2006.
- [22] Liangjia Zhu, Yi Gao, Vikram Appia, Anthony Yezzi, Chesnal Arepalli, Tracy Faber, Arthur Stillman, and Allen Tannenbaum, "Automatic Delineation of the Myocardial Wall From CT Images Via Shape Segmentation and Variational Region Growing," *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING*, VOL. 60, NO. 10, OCTOBER 2013.
- [23] E. M. van Rikxoort, I. Isgum, Y. Arzhaeva, M. Staring, S. Klein, M. A. Viergever, J. P. W. Pluim, and B. van Ginneken, "Adaptive local multi-atlas segmentation: Application to the heart and the caudate nucleus," *Med. Image Anal.*, vol. 14, no. 1, pp. 39–49, 2010.
- [24] X. Zhuang, K. S. Rhode, R. R., D. J. Hawkes, and S. Ourselin, "A registration-based propagation framework for automatic whole heart segmentation of cardiac MRI," *IEEE Trans. Med. Imag.*, vol. 29, no. 9, pp. 1612–1625, Sep. 2010.