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Research Article

A NOVEL TECHNIQUE FOR AUTOMATIC SEGMENTATION OF THE LEFT VENTRICLE FROM CARDIAC MR IMAGES

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ABSTRACT

Automatic LV myocardial boundary segmentation from Magnetic Resonance (MR) images is a challenging task. Manual segmentation of wall structures from different cardiac medical imaging modalities such as computed tomography (CT) and magnetic resonance imaging (MRI) is both labor intensive and time consuming. In this paper, an automated method for segmenting the Left Ventricle (LV) from Cardiac MRI images using Canny Edge detection technique and Active Contour Model. Initially, edge detection using edge gradient and edge map of the input image is used to identify the Region of Interest (ROI). Then, a local Gaussian distribution fitting energy is incorporated into the Active Contour model to extract the Left Ventricle. Interleaved level set evolution is used to achieve energy minimization by an iterative process. Gray-Level Co-occurrence Matrices (GLCM) are used to represent the segmented LV images. Morphological texture based features are extracted from the image are fed to an SVM classifier which is then used to identify any abnormality.

Keywords: Magnetic Resonance, Manual Segmentation, Computed Tomography, Gaussian Distribution.

INTRODUCTION

Cardiovascular disease is one of the leading causes of death in the world. Diagnosing and subsequent treatment of these pathologies rely on numerous imaging modalities like echo graphy, computed tomography (CT), coronary angiography, and magnetic resonance imaging (MRI). Most of the cardiac pathologies involve the left ventricle (LV) for the evaluation of left ventricular functions of the heart. Segmentation of the left ventricle would help to estimate the cardiac functional parameters such as the ejection fraction and myocardial mass. Mostlyin cardiac MRI images, poor contrast between LV blood pool and myocardium wall provides minimal edge information. This, added to similar intensity distributions in different regions proves to be a very challenging task in the segmentation of the LV when using only low level information such as intensity, gradient, etc. In such a scenario, inclusion of prior shape information provides immense significance in LV segmentations.

In recent years, a good many number of methods have been proposed for LV segmentation. Some of the methods are graph cuts[1], various deformable models[2,3], morphological operations[4], and shortest path algorithms[5]. Each of them provide novel techniques but each have different drawbacks due to high variation in the challenges of segmentation. Classical graph cut segmentation techniques use consecutive interaction for efficient and accurate segmentation in complex images[6-9]. This type of process utilizes image pixels a priori known to be a part of the object or background, which are introduced as topological constraints. In the case of complex images, the amount of time needed for this pixel accurate work makes image segmentation particularly challenging. Further, delineation of the boundaries of objects in medical images requires smooth and a continuous working space. In[10], interpretations of graph cuts have been done as hyper surfaces or contours in N-D manifolds in discrete image domains. But finding a smooth boundary separating the regions through the min cut of the graph presents a major problem. The paper attempts to solve this problem by using"fine" locally connected grids.

A good review of major active contour models can be found in Refs[12,13]. Edge-based models utilize image gradient to guide curve evolution, which are usually sensitive to noise and weak edges[11]. Instead of utilizing image gradient, region-based models typically aim to identify each region of interest by using a certain region descriptor, such as intensity, color, texture or motion, to guide the motion of the contour[14]. Recently, local intensity information has been incorporated into the active contour models[15-17] for more accurate segmentation, especially in the presence of intensity in homogeneity. Texture based feature extraction methods are described in[18]. A tutorial on image classification using Support Vector Machines is presented in[19].

In this study, a new framework is proposed for the auto-segmentation of the LV endocardium boundary in MRI images. First, Canny edge detection algorithm is used to detect the circular edges in the image. The biggest circular region is identified as the Left Ventricle. Aregion-based active contour model in a variational level set formulation is used for image segmentation. By using a kernel function, we first define a local energy to characterize the fitting of the local Gaussian distribution to the local image data around a neighborhood of a point. The local energy is then integrated over the entire image domain to form a double integral energy: local Gaussian distribution fitting (LGDF) energy. The local intensity means and variances, which are spatially varying functions, are two variables of the LGDF energy functional. The LGDF energy is then incorporated into a variational level set formulation with a level set regularization term.

In the resulting curve evolution that minimizes the associated energy functional, the local intensity information is used to compute the means and variances and thus guide the motion of the contour toward the endocardium boundary. It is then assumed that the epicardium is similar to the endocardium in shape. Then we construct an energy to characterize this similarity, using the endocardium result as reference..This shape similarity energy is implemented using the initial contour, i.e., the endocardium result, as reference. By this method, the epicardial wall is segmented and hence the Left Ventricle can be segmented from the image. Gray-Level Co-occurrence Matrices (GLCM) are used to represent the segmented LV images. Morphological Texture based features are extracted from the segmented. Feature Ranking is done using Linear Discriminate Analysis (LDA). The selected features are then used to train a linear SVM classifier that can be used to detect any abnormality. Normally, the left ventricular free wall is thickest at the cardiac base and it gradually becomes thinner towards the apex. At the very tip of the ventricle, the musculature is only 1–2 mm thick, even in hypertrophied ventricles. The normal thickness at the obtuse margin of the left ventricle for an adult heart is 12–15 mm, excluding trabeculations, when measured approximately 1.5 cm below the mitral hinge line (annulus).Patients with acute transmural infarction have been observed to result in an immediate abnormal increase in wall thickness associated with persisting abnormal post-systolic thickening.

The remainder of this paper is organized as follows. In section II, the proposed method for automatic Left Ventricle segmentation using Canny Edge detection technique and Active Contour Model using local Gaussian distribution fitting energy is described. In section III, extraction of the texture based features from the segmented image using GLCM and feature ranking using LDA is described. Section V describes the SVM based classification for detection of abnormality. Section VI gives concluding remarks.

Left Ventricle Segmentation

The purpose of edge detection in general is to significantly reduce the amount of data in an image, while preserving the structural properties to be used for further image processing. The canny edge detector first smoothes the image to eliminate and noise. It then finds the image gradient to highlight regions with high spatial derivatives. The algorithm then tracks along these regions and suppresses any pixel that is not at the maximum (non-maximum suppression). The gradient array is now further reduced by hysteresis. Hysteresis is used to track along the remaining pixels that have not been suppressed. Hysteresis uses two thresholds and if the magnitude is below the first threshold, it is set to zero (made a nonedge). If the magnitude is above the high threshold, it is made an edge. And if the magnitude is between the 2 thresholds, then it is set to zero unless there is a path from this pixel to a pixel with a gradient above T2.

The Canny Edge Detection Algorithm

The algorithm runs in 5 separate steps:

1. Smoothing: Blurring of the image to remove noise.
2. Finding gradients: The edges should be marked where the gradients of the image has large magnitudes.
3. Non-maximum suppression: Only local maxima should be marked as edges.
4. Double thresholding: Potential edges are determined by thresholding.
5. Edge tracking by hysteresis: Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge.

The output of Canny edge detection identifies the ROI. All closed loops are detected and the largest loop can be identified as the Left Ventricle.

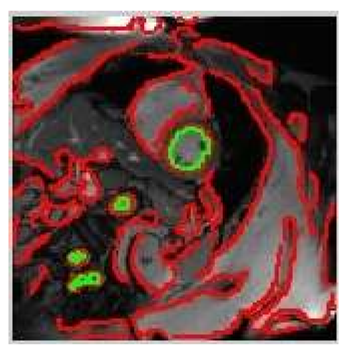
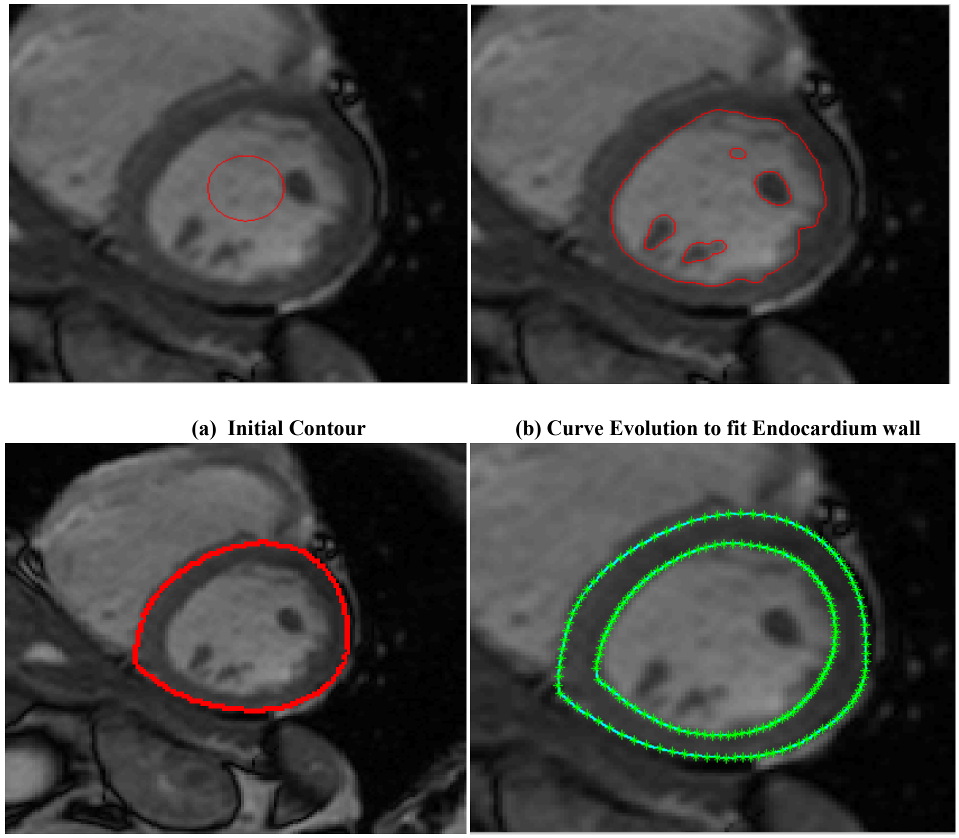


Figure 1: Canny Edge Detection Output

Active contours, are curves defined within an image domain which can move under the influence of internal forces coming from within the curve itself and external forces computed from the image data. The internal and external forces are defined so that the snake will conform to an object boundary or other desired features within an image.

In this paper, we propose an implicit active contour model based on local intensity distribution. To effectively exploit information on local intensities, we need to characterize the distribution of local intensities via partition of neighborhood. In this method, the LGDF energy is defined as a double integral: the first integral is defined with a kernel function to characterize the fitting of the local Gaussian distribution to the local image data around a neighbor- hood of a point; this local energy is then integrated to form the data term as a double integral in our variational formulation. Second, the local intensity means and variances, which are two variables of the proposed energy functional, are strictly derived from a variational principle, instead of being defined empirically.



(a) Initial Contour **(b) Curve Evolution to fit Endocardium wall**

(c) Epicardium Segmentation **(d) Left Ventricle Segmentation**

Figure 2: Left Ventricle Segmentation Process

Feature Extraction

Texture is one of the important characteristics used in identifying objects or regions of interest in an image. Texture can be evaluated as being fine, coarse, or smooth; rippled, molled, irregular, or lineated. These features are calculated in the spatial domain, and the statistical nature of texture is used based on the assumption that the texture information in an image is contained in the overall or "average" spatial relationship which the gray tones in the image have to one another. A set of gray tone spatial-dependence probability-distribution matrices are computed for the given image block and suggest a set of textural features can be extracted from each of these matrices. These features contain information about such image textural characteristics as homogeneity, gray-tone linear dependencies(linear structure), contrast, number and nature of boundaries present, and the complexity of the image. These features are quickly computable.

All the texture information is contained in the gray-tone spatial-dependence matrices. Hence all the textural features are extracted from these gray-tone spatial-dependence matrices. We use the position operator “1 pixel to the right and 1 pixel down” to obtain the gray-level co-occurrence matrix (GLCM).The angular second-moment feature (ASM) is a measure of homogeneity of the image. In a homogeneous image, there are very few dominant gray-tone transitions. Hence the matrix for this image will have fewer entries of large magnitude. The contrast feature is a difference moment of the Pmatrix and is a measure of the contrast or the amount of local variations present in an image. The correlation feature is a measure of gray-tone linear-dependencies in the image. Several features can be measured as functions of distance and angle. There are a set of 28 features out of which some of the features are strongly correlated with each other. A feature-selection procedure is applied to select a subset or linear combinations of these features.

Feature Ranking using Linear Discriminate Analysis (LDA)

Feature selection is the technique of selecting a subset of relevant features for building robust learning models by removing most irrelevant and redundant features from the data, feature selection helps improve the performance of learning models by:

- Alleviating the effect of the curse of dimensionality
- Enhancing generalization capability.
- Speeding up learning process.

•Improving model interpretability

LDA methods are used in statistics, pattern recognition, and machine learning to find a linear combination of features. LDA attempts to express one dependent variable as a linear combination of other features or measurements.LDA explicitly attempts to model the difference between the classes of data. Combination is based on differences rather than similarities. LDA searches for those vectors in the underlying space that best discriminable among classes. More formally given a number of independent features relative to which the data is described, LDA creates a linear combination of those which yields the largest mean differences between the desired classes.

SVM Classifier

Clinicians use cardiac MRI to perform volumetric measurements of anatomical structures, such as left/right ventricular end-diastolic/end-systolic volumes, mass, stroke volumes, and ejections fractions. However, these measurements are often not sensitive enough to detect certain cardiac disease as they do not fully utilize the rich information provided by cardiac MRI. In addition, clinicians often find it difficult to produce reliable prediction of disease progression due to the high inter- and intra-rater variability associated with these measurements. We address this issue in this paper by suggesting an alternative approach for detecting heart diseases by extracting high-dimensional textural features from the images and feeding hem into a classifier. The classifier automatically labels the image, which in our case corresponds to differentiating cardiac MRIs of patients effected by a certain disease.

The embedding coordinates of each image are fed into classifier, which labels each data set based on those features. We choose the support vector machine (SVM)classifier [8] for this task. SVM is a popular approach pattern classification. It separates the data into two clusters hopefully representing the healthy and diseased population. This separation is described through a hyper plane. The hyper plane is generated by training the algorithm on a pre-classified training set. From this training set, the algorithm selects a relatively small number of samples that are close to the opposite group. These samples are called support vectors and are used for defining the dividing hyper plane.

While the SVM classifier is very effective in finding this hyper plane, selecting he type of hyper plane is very important. If the hyper plane is too stiff then the algorithm might not perfectly separate the two groups. On the other hand, if the hyper plane is too flexible then the algorithm will over fit the data. The typeof hyper plane is characterized by the kernel that maps the data to a higher dimensional where linear separation is possible.

CONCLUSION

In this paper, we have presented an automated framework for Left Ventricle Segmentation by using Canny Edge detection technique for ROI identification and Active contours driven by local Gaussian distribution fitting energy. We have also attempted a disease classification frame work to diagnose abnormality of cardiac myocardium in patients. We extracted texture based properties from the cardiac MRI image and used LDA for feature selection. SVM classifier has been used for classification of abnormal Left Ventricle myocardium conditions. In the future, we will try for more accurate classification by taking more both spectral and textural features from the cardiac MRI image.

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