Automatic Detection of Left Ventricular Aneurysms in Echocardiograms

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ABSTRACT

Left ventricular cardiac aneurysms are bulgings in the myocardium muscle of the left ventricle. These irregular distortions of the left ventricular shape from its normal bullet-like appearance, are often due to result of myocardial infarction and can be fatal. In this paper we address, for the first time, the automatic detection of left ventricular (LV) cardiac aneurysms from 4-chamber views in echocardiograms. For this, we first detect the left ventricle in the echocardiogram image as the lumen region closest to the apex of the heart. The apex itself is estimated from the bounding lines of the viewing sector in an echocardiogram. The boundary of the LV is then analyzed to extract key curvature-based features for discrimination using a support vector machine with radial basis function kernels. Results of testing on a large echocardiogram video collection indicate that robust detection of left ventricle coupled with curvature features is sufficient to reliably separate LV aneurysms from normal left ventricular shapes.

Index Terms— cardiac aneurysms, curvature feature, LV detection, computer-aided diagnosis

1. INTRODUCTION

Left ventricular cardiac aneurysms are distortions or bulgings of the cardiac muscle surrounding the left ventricle. These often occur as a result of a prior myocardial infarction, hypertrophic cardiomyopathy or Chagas disease [12]. In myocardial infarction, the aneurysms are formed by a weakening of the heart muscle where trapped blood inflates the weakened flap of muscle into a bubble as shown in Figure 1b. Cardiac aneurysms can be fatal since the heart muscle containing the aneurysm is dyskinetic leading to an overall decrease in heart function. This results in congestive heart failure, and other diseases including thrombus, and ventricular tachycardia leading to sudden death.

Despite its importance, automatic detection of this problem has not received adequate attention in the medical imaging community. The gold standard for diagnosing LV aneurysms by cardiologists is through echocardiography [12]. In 4-chamber views, these bulges appear as significant distortions of the left ventricle from the normal bullet-like shape as shown in Figure 1b. Methods are needed to automatically analyze these shape distortions. This presupposes, however, that the left ventricular region can be reliably isolated, which in 2D echocardiography has proved to be difficult.

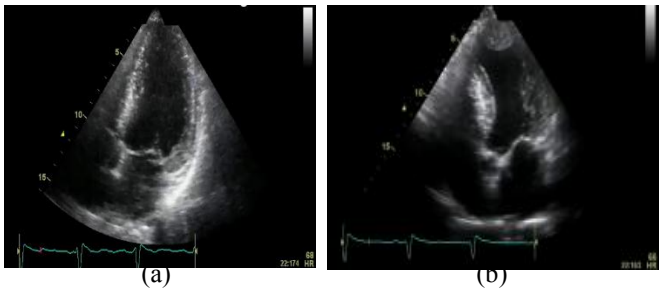

Figure 1. Illustration of cardiac aneurysm in echocardiograms. (a) Normal left ventricle, (b) LV aneurysm.

In this paper we develop a new algorithm to automatically detect left ventricular aneurysms in 4-chamber views of echocardiogram images. For this we first develop a robust method of extracting the left ventricular region in 4-chamber views by using the key idea that the lumen region closest to the apex of the heart depicted in these views is the left ventricle. The apex itself is estimated from the bounding lines of the viewing sector detected through feature detection in image-based rendering of the Hough Transform. The lumen region is isolated using a variant of multi-level Otsu thresholding [13]. The echocardiogram sequence information is used to robustly locate the contour of the left ventricle through the heart cycle. Using the apex as the reference point, the left ventricular boundary is regularly sampled and a 6-dimensional scale-invariant feature vector is formed by noting the curve position, angle of curvature, orientation of the bisector, and the orientation of the two incident lines at a point along the curve. These feature vectors from labeled training videos of normal and left ventricular cardiac aneurysms were then used to train a support vector machine classifier using radial basis function kernels and unlabeled sequences were then classified.

2. RELATED WORK

Although we are not aware of work that uses shape descriptors to detect LV aneurysms in 2D echocardiography sequences, there are many methods available to detect and describe left ventricles. In medical imaging community, the left ventricular (LV) shape has been modeled primarily for the purpose of segmenting the left ventricle in

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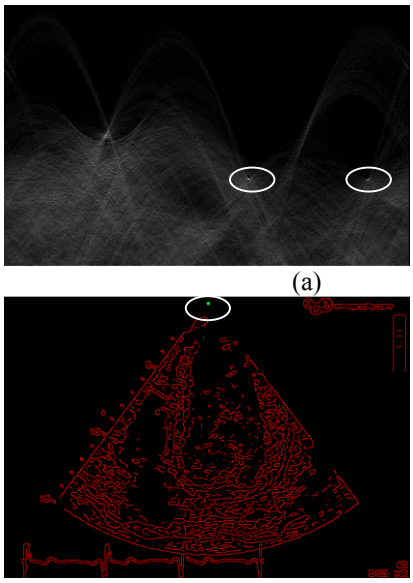
echocardiography images using a variety of techniques including active shape and appearance models [3, 4, 5], snakes and active contours [6,9], parametric shape descriptors of endocardial contours[8], deformable models and templates [6], level set techniques, etc. Model-based approaches such as active shape models are difficult to learn from a class of shapes as they need manual marker identification as well as prior registration of shapes during model training. The model is used to both localize and recognize the left ventricle, and frequently has localization errors, particularly for diseased states of the LV. Recently, the LV has been modeled as a prolate-spheroidal function and used to approximate normal LV shapes [14]. In that paper, an approach was also presented to localize the left ventricle using an initial K-means clustering of binarized echocardiogram images [14]. Using binary images and K-means clustering, only a rough localization can be made and precise LV contours as needed for shape description will be difficult to obtain. Finally, many descriptors for LV have been available including measures for ejection fraction [11], LV volume [11], aspect ratios from eigenvalues [15], and more recently, the deviations from prolate-spheroidal representations [14].

3. LOCALIZATION OF LEFT VENTRICLE

The key idea to localize the left ventricle proposed in this paper is to consider a lumen region that is close to the apex of the heart in a 4-chamber view. The apical four chamber view is generated by placing the transducer on the apex of the heart, near the apical impulse. A good apical 4-chamber view shows the septal and lateral free walls and the apex of the left ventricle. In an ideal apical four chamber view, the apex of the left ventricle is at the center of where the septum and lateral wall meet. In echocardiogram images, for the purpose of LV localization, a good estimate of the apex of the heart could be formed from the point of intersection of the bounding lines of the viewing sector.

3.1 Estimating the apex of the heart: The ultrasound scan sector in the image is usually bounded by dominant lines as can be seen from the edge image of Figure 2b.

Using a Hough transform the lines that go through every pixel (x0, y0) can be described by (r,θ), where $r(\theta) = x_0 \cos\theta + y_0 \sin\theta$. The dominant lines will have the most votes from pixels so that when the Hough transform is rendered as an image, the brightest pixels correspond to the strongest lines. The bounding sector lines are then chosen as those lines that are bright spots on a horizontal line (i.e. have the same radius), and separated by a reasonable viewing angle (80-120 degrees). The point of intersection of the bounding line gives the best estimate of the apex as shown in Figure 2b for the image of Figure 1a. Using the bounding sector lines, and the apex estimate, a triangular region of interest (ROI) can be formed for further processing.



(a)

(b)

Figure 2. Illustration of apex of the heart estimation in 4-chamber view echocardiogram image. (a) Hough transform on the lines seen in (b) The bounding lines and their intersection point are show circled in both images.

3.2 Extracting lumen regions:

We extract the lumen region of the left ventricle by thresholding the intensity in the ROI. In medical imaging, the main anatomical regions of interest are blood, tissue, fat, air and bone. Of these, only the first 4 are relevant for echocardiography, and hence we divide the image into regions of 4 different intensities. Using the multi-level Otsu algorithm [13] , we partition the image intensities into 3 optimal levels {t1, t2, t3}, which divide the original image into 4 classes: C1 for [1,…, t1], C2 for [t1+1, …, t2], … , C3 for [t3+1, …, L], where L is the maximum intensity level observed. The optimal thresholds $\{t_1^*, t_2^*, t_3^*\}$ are chosen by maximizing the inter-class variance σ_B^2

$$\{t_1^*, t_2^*, t_3^*\} = \arg\max\{\sigma_B^2(t_1, t_2, t_3)\} \quad (1)$$

Where $\sigma_B^2 = \sum_{k=1}^{3} \omega_k (\mu_k - \mu_T)^2$ and $\omega_k = \sum_{i \in C_k} p_i \quad \mu_k = \sum_{i \in C_k} i.p_i / \omega$. p_i is the probability of the grey level i in the image and μ_k are the class weighted means and μ_T is the overall mean. The left ventricle is then chosen as the region with intensity range [0,t1*]. These are the red colored regions in Figure 3b. Using a simple color connected component algorithm, we can group pixels of the same color to form the various regions. By retaining only those regions that are fully contained within the bounding sector lines, we are left with a few candidate regions for choice of left ventricle. The region closest to the apex of the heart among these selected regions is then taken as the left ventricle. Figure 3c shows the candidate region retained as the LV in Figure 3b. This

region can now be smoothed to enable robust feature detection for disease discrimination as shown in Figure 3d.

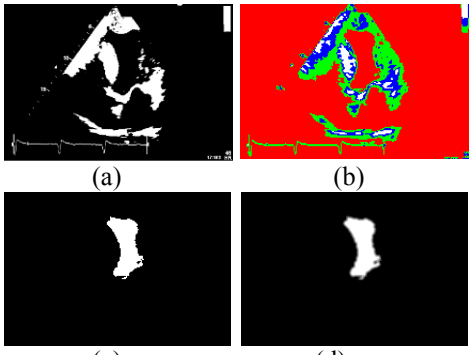


Figure 3. Illustration of single and multi-level thresholding to segment left verticle. (a) Otsu thresholding. (b) multi-level thresholding. (c) LV region extracted, (d) LV region smoothed.

Previous work on detecting left ventricle used binary Otsu thresholding [14]. As can be seen from comparing Figure 3a and 3b, the left ventricular contour is better detected using multi-level thresholding. Using the implementation described in [13], the intensity levels for segmenting the left ventricle can be estimated very quickly.

3.3 Integrating sequence information: To more robustly locate the left ventricle, and to more accurately estimate the shape changes due to the disease, we integrate the information across detections made in consecutive echocardiogram images of a heart cycle. The heart cycle itself is estimated from two sources, (a) using optical character recognition of the numbers next to the symbol 'HR' in the image (lower right corner in Figure 1a), and (b) from the synchronizing EKG trace that is present in the echocardiogram image using an image-based ECG periodicity estimation algorithm described in [16]. Thus the LV detection is initiated in each consecutive frame in the heart cycle as shown in Figure 4 and the smallest LV region which is detected at the closure of the mitral valve is retained as the best estimate of the LV region.

4. LV ANEURYSM DETECTION

Once the LV region is obtained, its contour can be detected by simple boundary following methods. The curve of the contour can then be sampled to extract features for discrimination. Since aneurysms are bulges in the contour of the left ventricle, we develop a 5-element feature vector per segment that is designed to outline the bulge. Specifically, we divide the LV contour into N segments with each segment describing a corner included in the segment L_i by the following 5 element feature vector:

$$\{L_i\} = \{(x_i, y_i, \theta_i, \rho_i, \alpha_i, \beta_i)\}$$

where θ_i is the angle in the corner, ρ_i is the orientation of the bisector, α_i, β_i are the orientations of the incoming and outgoing lines, and (x_i, y_i) is the position of the corner as shown in Figure 5.

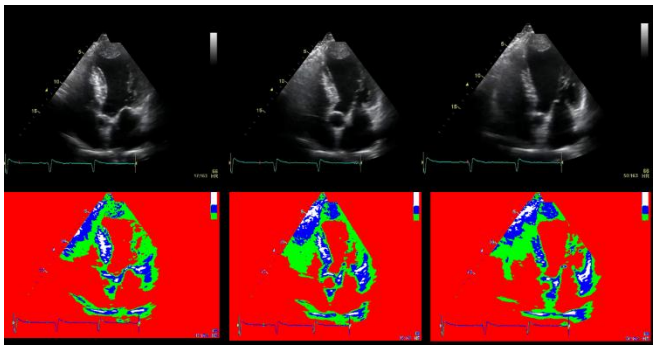


Figure 4. Illustration of LV detection through multi-level thresholding at key time points in the heart cycle.

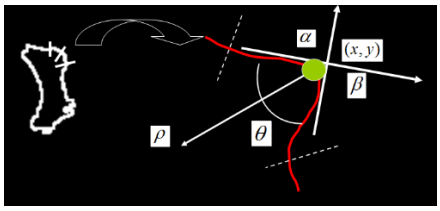


Figure 5. Illustration of feature extraction from LV contours for aneurysm detection.

4.1 Accounting for shape variations: Since no two LV aneurysms would be identical in appearance, the above feature descriptor must be made robust to individual shape variations all of which still signify local bulges characteristics of aneurysms. For this reason, we bring the LV shapes into rough alignment prior to the computation of features. Specifically, we account for scale variations by sampling the LV contour into N segments each. This also ensures that all feature vectors produced from different patients are of equal dimensions (N x 6) for subsequent learning. All LV contours are aligned to a reference LV contour using a similarity transformation (translation, rotation, scale) to account for global deformations and the transformed coordinates are used in the computation of (x_i, y_i). No deformable registration is performed to preserve the local changes in shape needed for recognition of the aneurysm. Finally, the sampled LV segments are aligned along the contour by using a common reference point for starting the generation of N segments. This reference point is chosen to be the point of intersection of the LV contour with the line joining the apex of the heart to the centroid. Once the LV contours are aligned, this determines a stable reference point to begin the sampling.

4.2 Learning to discriminate LV aneurysms: Using the ground truth normal/aneurysm labels provided for the underlying echocardiographic sequences during training, a support vector machine (SVM) is used to separate the feature

vectors of the aneurysm cases from normal data using the feature vectors described above. Given a new image, its feature vector is then classified using the learned SVM model. To enable robust classification, we select best LV contour per heart cycle and repeat the classification per heart cycle. The majority label produced from the LV contour of each successive heart cycle is used to determine the overall label for the echocardiogram video sequence as depicting an aneurysm or a normal left ventricular shape.

5. RESULTS

We now describe results of discrimination between normal and LV aneurysms in 4-chamber views of echocardiographic sequences. Our dataset consists of a total of 340 patients and 2158 echocardiographic sequences depicting a variety of cardiac diseases including aneurysms, dilated cardiomyopathy, hypertrophies and normal patients. Of these, about 400 sequences labeled as normal LV size and function from their corresponding reports and 254 sequences were labeled as depicting aneurysms.

5.1 LV aneurysm detection accuracy:

We tested the LV aneurysm detection accuracy using the SVM classifier by varying the choice of kernels and the amount of training data. By varying the amount of training data from 20% to 80%, the specificity ranged from 78% to 92% while the sensitivity was around 77%. The results are shown in Table 1. The radial basis function kernel was retained as the best performing kernel to separate the two classes.

Training Normals	Training Aneurysms	Test Normals	Test Aneurysms	Correct Detections	False Detections	Sensitivity	Specificity
52	72	348	182	412	117	77.8	78-92%

Table 1. Illustration of LV aneurysm detection accuracy.

LV Detection method	Dice coefficient %
Otsu thresholding	54.15
Otsu thresholding with K-means clustering	87.45
Atlas-based segmentation	67.32
Multi-level thresholded Apex-based LV detection	92.34

Table 2. Comparison of LV detection methods

5.2 Evaluation of LV detection accuracy:

As we could not locate prior work on automatic detection of LV aneurysms, we focused the comparative evaluation on the detection and extraction of LV contour. Since the feature vectors and hence the accuracy of our classification is dependent on the isolation of the correct LV contour, we evaluated the performance of LV contour identification in comparison to existing methods. This used ground truth data generated by our clinical expert who manually annotated the left ventricle in these cases. We compared the performance to three techniques, namely, (a) pure Otsu thresholding, (b) Otsu thresholding with K-means clustering [14], and (c) atlas-based segmentation [7]. The overlap of LV detections were measured using Dice coefficient.

Our results are given in Table2. From these results, we can see that the LV bounding contour extraction by our method gives the best overlap with the ground truth contours.

6. CONCLUSIONS

In this paper we have presented a novel method of detecting left ventricular aneurysms in 4-chamber view echocardiographic sequences. Robust LV detection is made possible by detecting the apex of the heart and selecting lumen region closest to the apex. Features selected for discrimination capture essential elements of aneurysms in the form of bulges in the LV contour. Future work will explore the finer distinction between LV and pseudoaneurysms.

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