Cardiac Cycle Phase Estimation in 2-D Echocardiographic Images Using SVM

Lakshmi A S¹ | Nissa Surling S N²

¹(Electronics & Communication, Kerala University, Trivandrum, India, lakshmias1990@gmail.com)
²(Electronics & Communication, Kerala University, Trivandrum, India, nissasurling@yahoo.co.in)

Abstract—An Echocardiogram is a non-invasive procedure used to assess the heart’s function and structures. This paper proposes a new hybrid approach to estimate the cardiac cycle phases in 2-D echocardiographic images as a first step in cardiac volume estimation. Here analysis of the atrial systole and diastole events by using the geometrical position of the mitral valve and a set of image features is done. The proposed algorithm is based on an organization of image processing methods and Support Vector Machine as a classifier to robustly extract anatomical information. An original set of image feature is used and derived to recognize the cardiac phases. The aforesaid approach is performed in a denoising scenario. In this scenario, the images are corrupted with Gaussian noise distribution. This hybrid algorithm does not involve any manual tracing of the boundaries for segmentation process. The algorithm is realized as computer aided diagnosis (CADi) software. A dataset of 160 images that include both normal and infarct cardiac pathologies were used. An accuracy of 93 percentage and a 1.2s in terms of execution time of CADi application was reported in a cardiac cycle estimation task. The significant improvement of this paper is the introduction of a hybrid method and set of image features that can be helpful for automatic detection applications without any user intervention.

Keywords—Support Vector Machine; Cardiac Phase Cycle; CAD; Image features

1. INTRODUCTION

The incidence of chronic heart failure in humans is very high and as a result, the melancholy and lethality are also very high in all countries, regardless of the economic development level [37], [38]. The data on mortality caused by the chronic heart failure reveal that the five years mortality rate remains at an alarmingly high level of 50 percent [39]. Heart failure is, therefore, a major clinical problem. Echocardiography is a non-invasive procedure to examine the heart and the surrounding blood vessels [40]. By echocardiography, the physicians visually inspect the four cardiac cavities (left and right atria, left and right ventricle), inferior vena cava, aorta, mitral valve, tricuspid valve, aortic valve and pulmonary valve. The image of the left ventricle (LV) and the analysis of the cardiac cycle are of great importance to cardiac research and represent a valuable tool to clinically assess cardiac health. The automatic detection of cardiac phases is a first step in the diastolic and systolic volume computation task. Moreover, the echocardiography also allows for automatic or semiautomatic analysis based on image features. Gaasch and Zile [41] illustrated that the clinical examination cannot distinguish between diastolic heart failure and systolic heart failure. Instead, the instrumentality of the echocardiography makes it possible. Ramachandran et al. [42] implemented the optical flow technique to reveal the displacement between few control points set on the left ventricular wall in short-axis view along the cardiac cycle. They established a relationship between the magnitude of displacement and the ECG recording. Negrini et al. [43] kinetically reviewed the wall in each frame of the cardiac cycle in order to gather information about contractility and diastolic functions. They used the automatic detection of the LV contours through the cardiac cycle phases. Their method involves a threshold operation and a spatial filtering followed by an automatic ventricular contour tracking. Aase et al. [44] investigated the automatic detection of the QRS complex and also the automatic cardiac cycle separation in B-mode echocardiographic images. Their method is based on a curvature interpretation of the mitral annulus displacement identified by a deformable B-spline curve. The Generic Echocardiographic Timing Algorithm (GETA) was used to analyze the mitral annulus curve displacement and to estimate the time point of cardiac cycle start. Kachenoura et al. [45] proposed a combination of two methods to automatically detect the end diastole and end systole. The foremost method is based on the mean intensity variation in a region of interest (ROI) during the cardiac cycle. The second method uses the correlation coefficient values between the end diastolic image and the next frames in the cardiac cycle. Martin et al. [46] presented a semiautomatic method for the segmentation and the tracking of the mitral valve leaflet in both phases of cardiac cycle. The main drawbacks of their method are: 1) the inability of the algorithm to accomplish the segmentation when motion of the muscle is very fast, going from an image to the subsequent one and 2) the necessity of manual initialization of active contour model (called “the snake”) on the first image of the sequence.

All the classical segmentation algorithms alone require significant user interaction to segment LV and they have been combined with other segmentation techniques in hybrid schemes to minimize user intervention. These algorithms work for mid-ventricular view of LV, but have issues in basal and apical view. Based on this general finding, this paper proposes a new algorithm able to accurately estimate the cardiac cycle phases in echocardiographic images without involving any manual tracing of the boundaries for segmentation process. This paper mainly focused on the left ventricular cardiac chamber. The purpose of the study was to increase the recognition ability of the algorithm, so that it correctly a certain between atrial systole and atrial diastole. Detailed cavity geometry and the position of the mitral valve were assessed using denoising, binarization and edge detection techniques. The denoising operation was performed in the framework of additive Gaussian distributions. Here the...
The goal is not to develop a new denoising algorithm but to optimize the formalism for denoising images and to preserve anatomical details relevant from the clinical standpoint. To characterize the cardiac cycle phases, an original set of features were proposed and derived. The mitral valve position was described in terms of three image features: 1) the number of boundary pixels belonging to an identified boundary; 2) the height of the mobile rectangle mask which enclosed the useful contour pixels; and 3) the horizontal size of object’s boundary inside the mask. Image features were defined and computed for each image in our dataset by using edge detection. Lastly, a support vector machine (SVM) has been trained as a classifier for effective detection of the mitral valve position in the echocardiographic images. This method does not require the user intervention. Moreover, this hybrid method allows improving the time efficiency. The basic reason underlying this study arises from the finding that if the mitral valve annulus fails to properly connect with the leaflets, then the functioning of the heart may be compromised resulting in the mitral valve regurgitation and stenosis heart affection.

This paper is organized as follows. Section II describes the methods and techniques employed here and it also introduces a new recognition algorithm. Section III provides the experimental results and discussions. Finally, the conclusions and ideas for further developments are outlined in Section IV.

A. Experimental Algorithm and Case

Fig. 1 presents the flowchart of the proposed algorithm. The algorithm contains three parts. In the first part, the images are processed using the denoising, binarization and segmentation techniques. A set of image features was extracted in the second part. In the third part, each component of the feature vector was assessed for both the analyzed cardiac phases and then the images belonging to the database were classified by the instrumentality of an SVM.

In order to evaluate the capability of our method to non-invasively gather all information about the position in motion of the mitral valve, frames of cine ultrasound data of human heart were used. One hundred and fifty images that include too wide to close properly. Also, dead tissue and scarred tissue which may occur after myocardial infarction do not contract and impaired on the mitral valve position. All images were acquired in vivo using the VIVID E9, GE HORTEN M OK WAY scanning systems (functioning in the Laboratory of Cardiovascular Imaging and Dynamics, Catholic University of Leuven, Leuven, Belgium). The 256 pixels images with 8 b/pixel DICOM were used. The hardware of the experimental environment was an Intel (R) Core (TM) 2 Duo CPU T 5900, 2.20 with 3-Gb RAM, operating Toolbox Processing Image and Neural Networks within MATLAB R2009a (the Mathworks Inc., Natick, MA). The statistical data analysis was performed using the SPSS ver.17 software (SPSS Inc., Chicago, IL).

B. Image Denoising

Removal of noise is shown to be a crucial step in imaging cardiac disease diagnosis. An efficient method for accurate noise filtration of the echocardiographic images is based on the Fourier transform (FT) and Gaussian low-pass filter (GLPF) [47], [48]. Here, the image processing is a three-step process: 1) the FT (1) is performed; 2) filtering the frequency components by using the GLPF (2); and 3) the inverse FT (3) is computed in order to reconvert the image to the spatial domain. Smoothing is achieved in the frequency domain by dropping out the high-frequency components and it is commonly used in edge detection when the algorithms are sensitive to noise.

The noise quality parameters, such as the signal-to-noise ratio (SNR), the peak signal-to-noise ratio (PSNR), the mean squared error (MSE), and mean absolute error (MAE) [47], [49], represent the quality indicators of the denoising process. A better denoising is characterized by higher values of SNR and PSNR parameters and lower values of the MAE and MSE parameters.

C. Binarization Methods

Otsu’s global binarization method was employed in order to automatically obtain a single optimal binarization threshold [50]. This technique divides the histogram of the image into two classes and calculates the optimum threshold T that separates these two classes so that their combined spread (intra-class variance) to be minimal. Otsu’s method searches for the threshold that minimizes the intra-class variance which is defined as the weighted sum of variances of the two classes. Here, it is based on treating the gray level intensities present in the image as values to be clustered into two sets, one foreground (black) and one background (white). The algorithm minimizes the weighted sum of within-class variances of the foreground and background pixels to establish an optimal threshold. This is equivalent to maximizing between class scatter. From this a scalar number, K is recurred. This is then used to binarize the image through the following equation:

\[ I_{bin}(x, y) = \begin{cases} 1, & \text{if } I_{gray}(x, y) \leq K \\ 0, & \text{if } I_{gray}(x, y) \geq K \end{cases} \]

D. Image Segmentation and Edge Detection

The Canny detector is widely considered as being the optimal boundary detector. The contour map of the studied object is computed using an algorithm consisting of five steps: smoothing (the noise can be removed in an effective way), finding the gradients (we are looking for gradients of

Figure 1. Flowchart of the algorithm
large magnitudes), the non maximum suppression (edges are marked using the local maxima), double thresholding (the possible edges are identified by thresholding), and the hysteresis (the chosen edges are validated by exclusion of the weak or not connected edges) [51]. As is well known, the Canny detector is looking for intensity discontinuities but it provides too many possible boundaries. It produces spatially extended outputs and we used these outputs to reduce the search space by selecting a satisfactory contour. A threshold value N is chosen in order to hold the core boundary (when the contour pixel number is higher than N) and to discard those boundaries classified as isolated (for which the contour pixel number is lower than N). By successive removal of isolated boundaries, the image is dilated and simplified. The optimal value of threshold N was established by maximizing the expected accuracy of CADi. The supreme objective is to have an algorithm, which knows where one object stops and another starts.

E. Feature Extraction

In our study, the classification process is not globally focused on the entire image of the LV. To classify the position of the mitral valve, an ROI with rectangular shape has been identified. The entire image is scanned by using a mobile rectangular mask with height of H pixels and width identical to the image width. The coordinates of the left corner of the sliding mask are (1, h), where h ∈ [1, image height - H + 1]. The scanning process identifies the regions of interest. ROIs consist of those rectangle areas which contain the highest number of contour pixels. The proposed image feature vector has two elements \( p = [p1 \ p2]^{T} \), where \( p1 \) is the maximum number of contour pixels (within the rectangle mask) used for computation and \( p2 \) represents the biggest horizontal length of the individual contours which are present inside the rectangular interest area. \( p2 \) is used to eliminate the small false regions.

F. Statistical t-Test

To validate the discernibility between the \( p1 \) and \( p2 \) feature classes of dataset belonging to two cardiac cycles, the t-test analysis was used [53]. The p value is a useful parameter able to discern whether the means of the two samples are significantly different.

G. Support Vector Machine

Support Vector Machines (SVM’s) are a relatively new learning method used for binary classification. The basic idea is to find a hyperplane which separates the d-dimensional data perfectly into its two classes. However, since example data is often not linearly separable, SVM’s introduce the concept of a “kernel induced feature space” which casts the data into a higher dimensional space where the data is separable. Generally, casting into such a space would cause problems computationally, and with overfitting. The main insight used in SVM’s is that the higher-dimensional space doesn’t need to be dealt with directly (as it turns out, only the formula for the dot-product in that space is needed), which eliminates the above matters. Furthermore, the VC-dimension (a measure of a system’s likelihood to perform well on unseen data) of SVM’s can be explicitly computed, unlike other learning methods like neural networks, for which there is no measure. Generally, SVM’s are perceptive, theoretically well-founded, and have shown to be virtually successful. SVM’s have also been extended to solve regression tasks (where the system is trained to output a numerical value, rather than “yes/no” classification).

Given l training examples \( x_i \), \( y_i \), \( i = 1, ...., l \) where each example has d inputs \( x_i \in \mathbb{R}^d \), and a class label with one of two values \( y_i \in \{-1, 1\} \). Now, all hyperplanes in \( \mathbb{R}^d \) are parameterized by a vector \( w \), and a constant \( b \), expressed in the equation

\[ W.X + b = 0 \]  

H. CADi Application

The CADi applications are tools developed to help physicians to detect various diseases and to reduce the workload of radiologists. One of most used feature of the CADi applications is the efficiency. The following parameters are considered when the efficiency of the CADi is evaluated: the sensitivity, the specificity, the accuracy, and the precision [18], [19].

- Sensitivity = \( \frac{TP}{P} \)
- Specificity = \( \frac{TN}{N} \)
- Accuracy = \( \frac{(TP+TN)/(P+N)}{TP/(TP+FP)} \)

where \( P \) denotes the total number of “positive” images and \( N \) the total number of “negative” images. Here, we considered the diastole cases as “positive condition” and the systole cases as “negative” condition. The correct diagnosis of a diastole image as “diastole” is a true-positive case (TP) and the incorrect diagnosis of diastole image as “systole” is a false-negative case (FN). Similarly, the correct diagnosis of systole image as “systole” is a true-negative case (TN) and the incorrect diagnosis of systole image as “diastole” is a false-positive case (FP). The optimal values of \( N \) and H parameters were estimated through the accuracy of the method.

3. RESULTS AND DISCUSSION

The experimental images were subdivided into two sets corresponding to two analyzed cardiac cycles (systole and diastole) by one trained radiologist physician. The expert manually labeled the images. This activity is labor-intensive and tiring. Note that the expert’s accuracy was 100%. Seventy-five systolic images and seventy-five diastolic images were used. The experimental echocardiographic images came from a blend of healthy and cardiac patients that suffer from myocardial infarction.

During the denoising operation, Gaussian noise with the mean in the range from 0 to 0.1 (with an increment step of 0.01) and variance in the range from 0.001 to 0.005 (with an increment step of 0.001) were deliberately added in 20 randomly chosen images. In our method, when the noise variance is more than 0.005, some details and edges of the image are smashed. Then, these images were denoised at various values of the D0 parameter. The optimal parameter of this approach can be either a maximum or a minimum, depending on the quality parameters of the noisy images. For additive Gaussian noise, an average optimal \( D0 = 0.3 \) was obtained by computing the optimum values characteristic to qualitative diagrams for each particular denoised experience.
Fig. 2 Denoising results a) Atrial diastole b) Atrial systole

Fig. 3 presents the binarized images using the automatic Otsu method. The binarization produces satisfying results and the myocardium walls are optimally highlighted. The image segmentation covers the contour-based approaches, and tries to exploit curvilinear continuity characteristics of the analyzed mitral valve structures.

Fig. 3. Images binarized using Otsu method a) Atrial diastole b) Atrial systole

Fig. 4 shows the edges detected by using the Canny method. Most of the major edges were detected but also lots of details have been emphasized and this can hamper the subsequent processing. In order to identify the position of the mitral valve, these images were scanned with a horizontal rectangle window having height H.

Fig. 4. Edge information by Canny detector and the rectangular scanning a) Atrial diastole b) Atrial systole

ROIs considered in our analysis contain the maximum number of contour pixels (p1 value). For diastolic phases, this condition is always accomplished when the mask scans the mitral valve in closed position. In the case of the systolic phase, this condition makes the mask not to stop when it scans the valve in open position. The mask will detect those regions containing the higher number of contour pixels. This drawback is minimized by using the second feature, p2, which helps the SVM to classify the images as diastole for higher value of p2 and as systole for lower value of p2.

Significantly smaller p2 and significantly larger p1 values were observed. An ideal recognition process of diastolic versus systolic phases must identify the significant differences between the components of the feature vector \( p = [ p_1, p_2 ]^T \). The T-test was applied to the following pairs of experimental results: 1) p1 of diastolic phase versus p1 of systolic phase and 2) p2 of diastolic phase versus p2 of systolic phase.

The recognition and classification results are strongly influenced by N (the threshold of Canny edge detector) and H (the height of sliding window) parameters. To obtain the threshold N value, the following idea is developed. When the mask scans LV in the systolic phase, the presence of the small, independent contours or edges having the contour pixel number lower than the threshold N leads to an increase of the feature p1 value. Therefore, the recognition process failed and the image will be misclassified as diastole. On the other hand, when higher values of the threshold N were used, the small, independent contours were removed. As a result, the value of the p1 feature decreased and the diastolic images were misidentified as systolic images. Concerning the height H of the scanning mask, the analysis presented in the following was made. If H has low values, the mask could fail to include the entire contours orientated more or less horizontal and finally, the values of the p2 parameter are low in diastolic phase images and a misclassification as systole can result. The higher H value of the rectangle mask would lead to overestimate the values of both p1 and p2 parameters and the final result is the misclassification of both systole and diastole analyzed cases. The optimal values of H = 20 and N = 180 were chosen.

When taking into account only the diastolic phase, in the first scenario the diagnostic performance of SVM for the differentiation is 93.8% (61/65) accurate. In the case of systole, the differentiation is 90.7% (59/65) accurate. This finding is readily explained by the entirely different appearance of the mitral valve in closed position.

<table>
<thead>
<tr>
<th>No</th>
<th>p1</th>
<th>p2</th>
<th>Classification result</th>
<th>No</th>
<th>p1</th>
<th>p2</th>
<th>Classification result</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>873</td>
<td>608</td>
<td>diastole</td>
<td>1</td>
<td>1439</td>
<td>602</td>
<td>systole</td>
</tr>
<tr>
<td>2</td>
<td>857</td>
<td>607</td>
<td>diastole</td>
<td>2</td>
<td>1396</td>
<td>659</td>
<td>systole</td>
</tr>
<tr>
<td>3</td>
<td>1009</td>
<td>318</td>
<td>diastole</td>
<td>3</td>
<td>1457</td>
<td>367</td>
<td>systole</td>
</tr>
<tr>
<td>4</td>
<td>1006</td>
<td>318</td>
<td>diastole</td>
<td>4</td>
<td>1431</td>
<td>528</td>
<td>systole</td>
</tr>
<tr>
<td>5</td>
<td>1178</td>
<td>331</td>
<td>diastole</td>
<td>5</td>
<td>1425</td>
<td>417</td>
<td>systole</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>gaussian</td>
<td>93.8%</td>
<td>90.7%</td>
<td>93%</td>
<td>90.2%</td>
</tr>
</tbody>
</table>

The experimental results proved good precision and effectiveness of our recognition algorithm in clinical studies. This proposed technique uses expert knowledge to detect the position of the mitral valve and SVM learns from in vivo data and does not need to be reprogrammed. Once SVM is trained, the detection becomes very fast. The calculated work time necessary to totally investigate an experimental...
image is 1±0.2 s so that the proposed CADi application facilitates a real-time classification. In routine practice, determination of systole and diastole frames is visual through slow animation of loops with a trackball. The manual labeling activity takes between 5 and 8 s per image.

Entirely automatic analysis becomes an attractive idea because it can eliminate the user variability and it can allow for an unsupervised and possible online quantification. In this respect, our proposed methods could be improved and extended. A multiobject outlook incorporating endocardium, epicardium, valves, atria, and vessels will improve the detection accuracy.

4. CONCLUSION

A new possible approach in the field of heart disease remote monitoring could offer patients a more individually focused care and, thus, an improved quality of life. The objective of this study was to develop a method capable of real-time estimate the cardiac cycle in LV echocardiographic image sequences. In a first step, the developed system used the denoising, the binarization, and the segmentation techniques. Then, an original method dealing with new proposed image feature sets for an analysis task was designed. In the second step, the SVM technique was employed followed by a CADI efficiency study. In order to obtain a computationally fast and efficient algorithm for cardiac cycle phase recognition, we have proposed a local approach, where an ROI of rectangular shape was identified. The approach presented previously benefits from the advantages of a new hybrid method, which couples additive and multiplicative noise removal with image processing and classification tools. Finally, we have showed that our hybrid strategy and the Gaussian noise distribution constitute a competitive solution for fast estimate of the cardiac cycle phases. An accuracy of 93% suggests a good performance of the proposed algorithm when an additive Gaussian noise distribution is considered.

REFERENCES


[18] Assoc.Prof.Dr.Cem Utsalan,EEE562,”Image Processing”.
[22] MATLAB-creating Graphical User Interfaces
[23] Jose I. Zamorano,”Echocardiography in the Detection and Monitoring of Heart Failure”.
[27] "Edge Detection",Slides from Cornelia Fermuller and Marc Pollefeys.
[29] Prof.P.K.Biswas,”Digital Image Processing”.

Volume: 02 Issue: 12 2015 www.ijmtes.com 12