ENDOCARDIAL SEGMENTATION IN CONTRAST ECHOCARDIOGRAPHY VIDEO WITH DENSITY BASED SPATIO-TEMPORAL CLUSTERING

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Abstract: We present a spatio-temporal clustering algorithm for detection of endocardial contours in short axis (SAX) contrast echocardiographic image sequences. A semiautomatic method for segmentation of left ventricle in SAX videos is proposed which uses this algorithm and at the same time requires minimal expert intervention. Expert is required to specify a few candidate points belonging to the contour, only in the first frame of the sequence. The initial contour is approximated by fitting an ellipse in the region defined by the points specified. This region is identified as the principal cluster corresponding to the left ventriclular cavity. Later the density based clustering was applied for regularization on the inital contour. We have extended the DBSCAN algorithm for identification of the principal cluster corresponding to the left ventricle from the image. The algorithm also incorporates the temporal information from the adjacent frames during the segmentation process. The algorithm developed was applied to 10 data sets over full cardiac cycle and the results were validated by comparing computer generated boundaries to those manually outlined by one expert. The maximum error in the contours detected was $\pm 2.9mm$. The spatio-temporal clustering algorithm proposed in this paper offers an efficient semiautomatic segmentation of heart chambers in 2D contrast echocardiography sequences.

1 INTRODUCTION

Amongst the various medical imaging modalities, two dimensional (2D) echocardiography is valuable for patients with heart diseases. It is noninvasive, real time, easy to use in clinical environment and offers relatively low cost solution as compared to other modalities (Bridal et. al, 2003). However, for evaluation of cardiac functional parameters, segmentation is to be carried out. Manual segmentation as routinely carried by experts is time consuming and tedious due to large image data in different standard echo views over a full cardiac cycle. Again the manual method also suffers from inter-observer and intra-observer variability in measurements (Maes et. al, 1993). Many researchers have shown image processing applications to enhance clinical utility of echocardiography by automated and semiautomated endocardial border delineation and for evaluation of functional cardiac parameters (Noble and Boukerroui, 2006). In fact there is a continuous growing demand for the automated segmentation and quantification to support professionals in diagnosis. In recent years automated segmentation of heart chambers and in particular the left ventricle has received significant attention in 2D and 3D echocardiograms. However automatic edge definition and subsequent segmentation in echocardiograhic images is difficult due to presence of speckle noise, poor contrast, inherent dropouts, inter-cavity structures and variability of data along with orientation and positioning of transducer (Setaredhan and Soragham, 1996).

In recent years numerous clinical studies have shown the clinical utility of myocardial contrast echocardiography (MCE) in quantification of myocardial perfusion, left ventricle (LV) volumes, LV contours and cardiac functional parameters (Cohen et.al., 1998). There have been few reports of research attempts towards the semiautomatic and fully automatic segmentation of left ventricle from 2D contrast enhanced echo images (Wolfer et. al, 1999). A very rigorous work for the segmentation problem

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in low mechanical-index contrast echocardiography is reported (Zwirn et. al, 2006). It has been shown that the use of temporal continuity results in better segmentation as it follows the approach of human expert in delineation (Mullet-Parada and Noble, 1998). Typically the dropouts present in the image can be recovered by the use of boundary information from the neighboring frames (Choy et. al, 1998). Researchers have reported active contour approach (Morales et. al, 2002), trained deformable models (Garcia et. al, 2003) and active shape model (Pickard et. al, 2004). Many of the proposed methods have shown results comparable to expert delineation for good quality images (Mishra et. al, 2003). However none of the methods has a generalized applicability for fully automatic or semiautomatic segmentation for the images acquired in routine clinical environment.

Few researchers have extended the application of well established data clustering approaches in the field of medical image segmentation (Celebi et. al, 2005). In this work we have extended the Density-based Clustering (DBSCAN) approach by including temporal data and applied for the segmentation of contrast echo sequences. Our spatio-temporal clustering algorithm has shown good results in the segmentation of endocardial borders in frames of a sequence by accommodating temporal information. The user intervention is minimal and is of the form of specifying five or more candidate points for contour on the first frame of the sequence.

The paper is organized as follows: In section II we discuss the density based clustering and its extension in spatio-temporal clustering technique. In section III, we present the application of the algorithm for segmentation of endocardial border after fitting the ellipse in the first frame through the points specified by the user and then to subsequent frames in the sequence. The contours thus obtained are post processed and smoothened to obtain final endocardial borders. In section IV we present the results of the proposed algorithm and, finally conclusions drawn and future work is discussed in Section VI.

2 CLUSTERING

Clustering is an important technique in data mining for finding data distributions and patterns in the underlying one or more dimensional data (Jain and Dubes, 1988). It has been a active field of research since last two decades and many novel approaches have been reported in the literature (Jain et. al, 1999). Clustering has number of upcoming application fields, such as statistical data analysis, pattern recognition, image processing, segmentation and many others. It is the task of grouping similar objects together with respect to a distance , connectivity, continuity, relative density in the space or other similarity measure.

In formal mathematical definition cluster is defined as (Fung, 2001): Let $X \in \mathbb{R}^{m\times n}$ be a set of data items representing a set of m points in x_i in $\mathbb{R}^n$. The goal is to partition X into K groups C_k such that every data that belongs to the same group are more alike than data in different groups. Each of the K groups is called a cluster. The result of the algorithm is an injective mapping $X \longmapsto C$ of data items X_i to clusters C_k. The number K might be preassigned by the user or it can be unknown determined by the algorithm . There are many approaches to data clustering that vary in their complexity and effectiveness. For our application we have focussed our attention on a single cluster $(K = 1)$, pertaining to the heart chamber specifically, the left ventricle in the contrast echcocardiographic view. In our work we call it as principal cluster. The assumption of defining only one principal cluster is valid because the spatial coordinates of the boundary objects of this principal cluster reflect the endocardial contour.

2.1 Dbscan for Principal Cluster

Density-based algorithms typically regard clusters as dense regions of objects in the data space separated by regions of low density. Thus the main objective lies in finding regions of high and low densities (Bradley and Fayyad, 1998). This approach is also capable of finding arbitrarily shaped clusters in the data space. Another advantage of these algorithms is that they are independent of the prior knowledge of the number of clusters. Hence these are very useful in situations very clustering can be confined to only in the region of interest (Han and Kamber, 1998). In contrast enhanced short axis echo sequence, the chamber cavities are filled with micro-bubbles which contribute in achieving their opacity. This results in a bright regions corresponding to the blood filled areas in an echo image (Fedele et. al, 1998). In the SAX images of the left ventricle (LV), a single bright region in the center of the acoustic window corresponds to the LV cavity. We treat this central bright region as a single cluster of interest. As stated earlier it is termed as the principal cluster for this application. The two global parameters of density based clustering algorithms are:

- Eps: Maximum radius of the neighborhood.
- $MinPts$: Minimum number of points in the Eps neighborhood of a point.

The ellipse fitted through the expert specified points in the first frames is taken as the starting point for the density based cluster algorithm. The maximum radius of the neighborhood Eps is chosen as half of the major axis of the ellipse. The parameter $MinPts$ was chosen to be 100 after a study of end systole images in 44 patients. The core point of the principal cluster is chosen as the center point of the ellipse fitted through the points specified by the expert in the first frame. We have chosen four local parameters for grouping the objects (pixels) in a cluster. These parameters include the features of the objects like pixel intensity, gradient threshold, gradient angle and the angular gradient with respect to the center point of the region. For cavity boundary, only negative intensity changes are identified along radial lines from center point. Again the threshold for gradient (G_T) was obtained automatically from the histogram statistics and the coordinates and intensities of the pixels specified by the expert. The algorithm for our application is framed as:

- *The center of the ellipse is taken as core point.*
- *The maximum radius is assigned the value of semi major axis in the first frame.*
- *Gradient threshold is obtained by histogram of the frame.*
- *Density reachable points around the core point are identified.*
- *Above steps are repeated for all the frames in the sequence.*
- *Border objects of the cluster are determined.*

2.2 Spatio-temporal Dbscan

An image is a 2-dimensional(2D) array of pixels defined on a $W \times H$ rectangular lattice $S = [\ (x,\ y) : 1 \le x \le W, 1 \le y \le H\ ]$, and is indexed by the coordinate $(x,\ y)$. Each pixel in a given frame can be represented by a feature vector. In a video stream, image frames are continuous along the time axis. Thus a video sequence can be expressed in spatio-temporal domain. Temporal dimension can be incorporated in many ways. One of the way is separating the frames of the sequence with respect to discrete time and to stack consecutively. We follow this approach in our application. In a video sequence, the frame to frame variation in shape and dimension of a given object depends upon its deformity and forces acting on it. Hence it is possible to recover a missing segment or to correct any outlier in the contour from the adjacent frames if the frame to frame variation is not significant. The outliers are detected with the radius of curvature of the extracted contour and the corresponding points in adjacent frames. We propose temporal continuity in the neighborhood of three frames:

1. For i^{th} frame the j^{th} border pixel will lie in the bounds setup by $(i-1)^{th}$ and $(i+1)^{th}$ frame.
2. Presence of drop out pixels in a frame was taken by temporal continuity from adjacent frames over an interval of three fames.

We have used parameter λ as the correction factor which governs the closeness of the corrected segment with the temporal frames. Correction is incorporated at 360 equidistant points on the contour i.e $j = [1, 2, ...360]$. The clustering is recursively carried out to regroup the cluster on the basis of modified distance and density parameters. These parameters in turn are function of λ during recursive calls of DBSCAN.

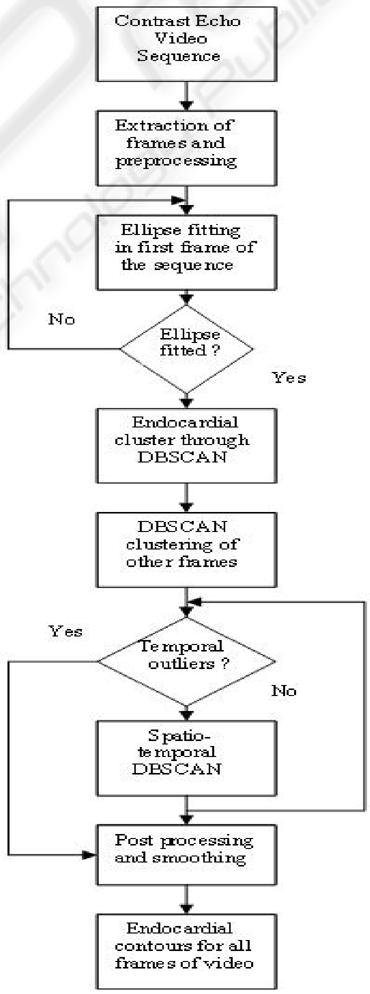

Figure 1: Flow chart for segmentation procedure.

3 SEGMENTATION WITH T-DBSCAN

In this work, we have applied the spatio-temporal clustering algorithm to segment the endocardial border in the contrast enhanced echocardiography videos of 10 patients. Figure 1. shows the flowchart of the segmentation procedure. After preprocessing of the image frames, user specifies candidate boundary pixels of the left ventricle in the first frame of the first frame of the sequence by mouse. The ellipse is fitted through these points and its parameters are stored for subsequent processing.

3.1 Image Processing

The echocardiographic videos used in this study were contrast enhanced short axis apical images at various levels of LV. These were obtained from different subjects for two to four cardiac cycles. The videos were acquired on GE Vingmed Ultrasound, VIVID7 in hospital environment under expert guidance. The frames in each video were 434 x 636 true color with 8 bit bitdepth in DICOM format. Gray scale conversion with 256 levels was done. The video sequences for one complete cardiac cycle were used for estimation of LV border. Echo images contain speckle noise which lead to incorrect gradient estimation. Hence speckle reducing anisotropic diffusion (SRAD) filtering was used (Yongjian and Scott, 2002). They have suggested edge sensitive diffusion for reducing speckles. In the numerical implementation we used $\delta t = 0.008$ and threshold of 5. This reduced the speckles and at the same time preserved the edge information for further feature extraction.

3.2 Elliptical Boundary Approximation

The Initial boundary approximation is carried out in the first frame of the sequence by fitting a ellipse through the points specified by the expert. The best fit ellipse through the points specified is done using Least Squares Criterion (Fitzgibbon et. al, 1999) A minimum of five points are to be specified by the expert, which strongly belong to the endocardial border for that particular frame. This is the only user intervention which is required in our scheme. The standard *impixel* function of MATLAB is used which gives the spatial coordinates of the selected points along with their intensities. The intensities returned by the function were used in the subsequent procedure for the search.

The generalized CONIC equation of the Ellipse is given by:

$$ax^2 + by^2 + cx + dy + exy + f = 0 \tag{1}$$

with a, b and c not all zero and $b^2 < 4ac$, where all of the coefficients are real. Again, more than one solution, defining a pair of points (x, y) on the ellipse, exists. It can be expressed in matrix notation as;

$$\mathbf{X^T A X} = 0 \tag{2}$$

where **X** and **A** are given by

$$\mathbf{X} = [1\ x\ y]' \tag{3}$$

$$\mathbf{A} = \begin{bmatrix} f & 0.5c & 0.5d \\ 0.5c & a & 0.5e \\ 0.5d & 0.5e & b \end{bmatrix} \tag{4}$$

The coordinates of the N chosen points ($N >= 5$) as marked by the expert and the equations (2-4) are used for the determination of the parameter matrix of the conic representation. The orientation and tilt of the ellipse is sought by coefficients in the equation (1) and incorporated in the evaluation of final ellipse parameters using square completion method. Figure 2 shows the first frame of SAX apical sequence with the detected ellipse and its center point.

Figure 2: Ellipse Fitted in the first frame of the sequence.

3.3 Spatio-temporal Clustering

The DBSCAN clustering algorithms is recursively called for incorporating corrections in the outliers with the parameter λ. In our implementation we have used $\lambda = 0.5$ distance units, which gave optimum results.

3.4 Post Processing and Smoothing

The contour thus obtained was smoothed out by locally weighted scatter plot smoothing using least squares linear polynomial fitting. A span of 10 *percent* was used to implement this standard

MATLAB function. Further smoothing was carried out by fitting spline through the data points with minimizing the maximum square distance between the data points.

Figure 3: Detected contour in frame No.1.

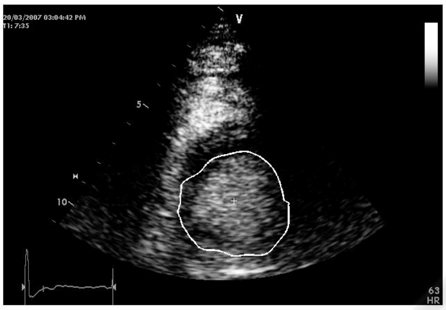

Figure 4: Detected contour in frame No.8.

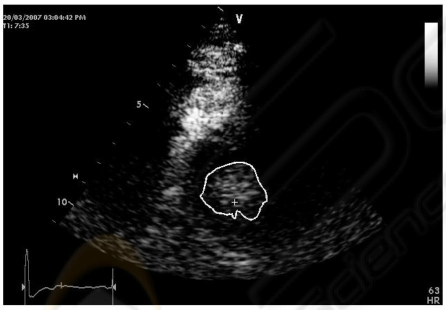

Figure 5: Detected contour in frame No.15.

4 EXPERIMENTAL RESULTS

The proposed methods for ellipse fitting, DBSCAN and Spatio-temporal DBSCAN were implemented in MATLAB 2006a on P-IV 2.1 GHz PC. Figures 3 to 7 show the result of application of the proposed algorithm. The endocardial border estimation was done on more than 10 video sequences of various standard contrast echo views. The contour estimated by computer in each frame of every sequence was compared with that drawn by expert.

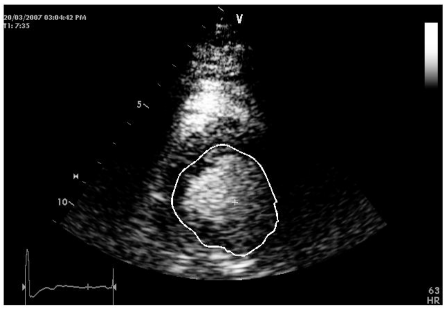

Figure 6: Detected contour in frame No.25.

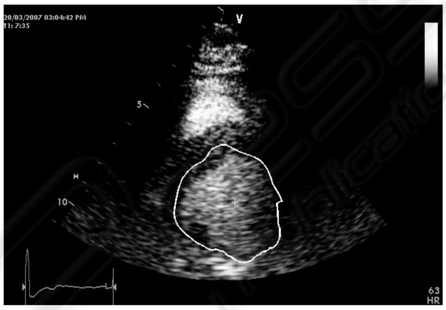

Figure 7: Detected contour in frame No.32.

5 CONCLUSIONS

The proposed method for semi automatic estimation of endocardial border of heart chambers in short axis contrast echocardiographic sequences is based on ellipse fitting and subsequent spatio-temporal recursive density-based clustering. The results show the effectiveness of the method and its utility in the recovery of the dropouts during image acquisition. The method requires user intervention only in the first frame of the sequence. The contour for each frame so obtained may be utilized for the determination of the cardiac parameters like, wall motion, area and for 3D visualization. Further work is required before the method can be employed in clinical environment for evaluation of cardiac functional parameters. The issues involved are the testing robustness, computational complexity of the method along with its sensitivity to the expert points. The algorithm requires fine tuning of parameter λ for determination of optimum number of iterations. In future work, we also intend to test the proposed method on large number of data sets for its further validation for images acquired in routine clinical environment.

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