Calculation of the Ejection Fraction (EF) from MR Cardio-Images

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Abstract

This paper outlines an algorithm to segment images on the short-axis view of the heart, obtained from multi- slice and multi-phase MR (Magnetic Resonance). Using the data from the segmentation of the slices, the ejection fraction of the heart is calculated for the given sequence. Segmentation is achieved by first filtering the images using Adaptive Smoothing, which smoothes the image without shifting the image edge information. The images are then segmented using unsupervised clustering, which finds homogeneous groups of data points in the data set. The left ventricle cluster from each slice is then rendered and the ejection fraction calculated.

Keywords: Ejection Fraction, segmentation, adaptive filtering, unsupervised clustering.

1 Introduction

According to the World Health Report 2002, 29% of all fatalities in their 191 member states were as a result of cardiovascular disease [A. Rodgers, 2002]. This 29% is then subdivided into ishehemic heart disease, which is found to be the largest, followed by cerebrovascular disease and hypertensive heart disease. Cerebrovascular disease is a clogging of the arteries to the brain and will not be dealt with in this paper.

Hypertensive heart disease is a late complication of hypertension (high blood pressure) that affects the heart and is commonly due to increased vascular resistance. High blood pressure adds to the workload of the heart, and over time, this can cause thickening of the heart muscle and the symptoms of hypertensive heart disease.

As the heart continues to pump against elevated pressure in the blood vessels, the left ventricle becomes enlarged, cardiac output (the ejection fraction) goes down, and without treatment symptoms of congestive heart failure may develop [US National Library of Medicine, 2003].

Ischemic heart disease is the clogging of the coronary arteries with plaque. This then reduces the amount of oxygen reaching the heart muscle (myocardium) which weakens the muscle and reduces its ability to pump, the ejection fraction goes down.

The acquisition of the ejection fraction (EF) of the heart is therefore important for early prognosis of cardiac disease. The ejection fraction is defined as "the proportion, or fraction, of blood pumped out of your heart with each beat"[NAPSE, 2001]. The blood that travels around the body is pumped from the left ventricle and therefore the volume of the left ventricle (LV) at the start of the heart stroke (the systole) and the end of the stroke (the diastole) is measured to give the cardio output(ml). The EF(%) is the amount of blood pumped as a percentage of the total volume of the LV at the diastole stage. The basic equation for finding the Ejection Fraction is given as:

$$EF = \frac{V_{endo}(t_D) - V_{endo}(t_S)}{V_{endo}(t_D)} \tag{1}$$

where V_{endo} is the volume of the inner walls of the heart, $V_{endo}(t_D) = max_t[V_{endo}(t)]$ is the end-diastolic volume and $V_{endo}(t_S) = min_t[V_{endo}(t)]$ is the end-systolic volume [Richard E. Klabunde, 2002].

Traditional methods for measuring the Ejection Fraction involved the physicians interpretation of echocardiograms or manual segmention of the LV and applying geometric approximations to find the volume i.e. Single Plane Ellipsoid, Biplane Ellipsoid, Hemisphere cylinder, Modified Simpsons Rule and Modified Teicholz model [Schuler, 2001][M. Dulce, 1993]. Dulce et al. [M. Dulce, 1993] showed that for a normal heart all models were sufficient in finding the LV volume, but for hearts with hypertrophy only Simpsons Rule and the Hemisphere cylinder gave acceptable results. All of the geometric models were tested against multi-phase, multi-slice data which was assumed to yield the most accurate results.

As well as being time-consuming, manual segmentation of the left ventricle is susceptible to large inter and intra-observer variations. There are many automatic and semi-automatic segmentation algorithms such as Active Contours or snakes [I. Mikić, 1998][M. Santarelli, 2003], Deformable Models [Rueckert and P. Burger, 1997], Active Appearance Models [B.P.F. Lelieveldt, 2001] etc. used to find and track the Left Ventricle. Such algorithms are still not found in clinical use but with the growing robustness and the development of software such as Geest's MASS [van. der. Geest, 2002] system the future of medical imaging will surely advance towards implementation in everyday cardiac analysis.

MR is the imaging modality used in this investigation. MR boosts many advantages over other imaging techniques employed in cardiac imaging. Unlike ultrasound and conventional Computer Tomography, MR produces increasingly high quality images, a wide topographical field of view and high soft-tissue contrast discrimination between the flowing blood and myocardium without the need for contrast enhancers [F. Frangi, 2001]or radiation exposure. MR can produce multi-slice images with high spatial resolution as well as multi-phase images at arbitrary imaging planes which sets it apart from angiocardiography [Brown and Semelka, 1995].

The multi-slice images can be ECG gated to produce images at different spatial positions but at the same point in the cardiac phase. The main difficulties include the presence of grayscale inhomogeneity, caused by attenuation of the radiofrequency wave by the tissue leading to a low signal-to-noise ratio, slice thickness taken at a coarse level resulting in lack of accuracy in volumes around the apex of the LV and artifacts in the blood [M. Santarelli, 2003].

2 Algorithm Overview

To calculate the ejection fraction two sets of multi-slice ECG-gated images from the short-axis were used, at both the systolic and diastolic phases. The images are taken from the volume slice by slice and smoothing and segmentation are then performed. The first images in both sequences are filtered using adaptive filtering to smooth the image, while still maintaining the unaltered edge information. Traditional methods of smoothing such as median or average filters blur the edges of the endocardium and thus producing false volume information.

Segmentation is performed on each slice using the k-means unsupervised clustering technique. This technique labels each region of the image with the grayscale average of that region. The user must select the region of the LV by clicking on it with the mouse. Once this cluster has being selected the remainder of the images in the volume are smoothed and segmented. The regions of interest are then connected using both the interslice region connectivity and the grayscale information.

The area of the LV is calculated for each slice and then summed to give the volume of pixels in both the systolic and diastolic phases and from these values the ejection fraction is calculated.

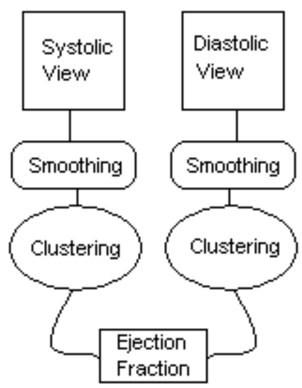


Figure 1: Process flow from original MR Images to Ejection Fraction

3 Adaptive Smoothing

The algorithm for adaptive smoothing implemented in this paper is adapted from Ke Chen [Chen, 2000]. The technique measures two types of discontinuities in the image, local and spatial. Local variable discontinuities can detect local intensity changes but is susceptable to errors where there is a lot of noise, so in addition to the local discontinuities the contextual information is also utilised using the attributes of neighboring pixels. From both these measures a less ambiguous smoothing solution is found. In short, the local discontinuities indicate the detailed local structures while the contextual discontinuities show the important features.

3.1 Local Variable Discontinuities

In order to measure the local discontinuities, four detectors are set up as shown:

$$E_{H_{xy}} = |I_{x+1,y} - I_{x-1,y}|, \tag{2}$$

$$E_{V_{xy}} = |I_{x,y+1} - I_{x,y-1}|, \tag{3}$$

$$E_{D_{xy}} = |I_{x+1,y+1} - I_{x-1,y-1}|, \tag{4}$$

$$E_{C_{xy}} = |I_{x+1,y-1} - I_{x-1,y+1}|, \tag{5}$$

$I_{x,y}$ is the intensity of the pixel at the position (x,y). We can then define a local discontinuity measure E_{xy} as:

$$E_{xy} = \frac{E_{H_{xy}} + E_{V_{xy}} + E_{D_{xy}} + E_{C_{xy}}}{4} \tag{6}$$

These pixel positions are illustrated below in Figure 2.

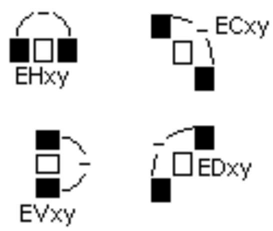


Figure 2: The four local discontinuity detectors of the Adaptive filter

3.2 Contextual Discontinuities

In order to measure the contextual discontinuities, a spatial variance is employed. First, a square kernel is set up around the pixel of interest, $N_{xy}(R)$. The mean intensity value of all the members of this kernel is calculated for each pixel as follows:

$$\mu_{xy}(R) = \frac{\sum_{(i,j)\in N_{xy}(R)} I_{i,j}}{|N_{xy}(R)|} \tag{7}$$

From the mean the spatial variance is then calculated to be:

$$\sigma^2_{xy}(R) = \frac{\sum_{(i,j)\in N_{xy}(R)} (I_{i,j} - \mu_{xy}(R))^2}{|N_{xy}(R)|} \tag{8}$$

This value of sigma is then normalised to $\tilde{\sigma}^2_{xy}$ between the minimum and maximum variance in the entire image. A transformation is then added into $\tilde{\sigma}^2_{xy}$ to alleviate the influence of noise and trivial features. It is given a threshold value of $\theta_\sigma = (0 \leq \theta_\sigma \leq 1)$ to limit the degree of contextual discontinuities.

3.3 Overall Adaptive Algorithm

Finally, the actual smoothing algorithm runs through the entire image updating each pixels intensity value I^t_{xy}, where t is the iteration value.

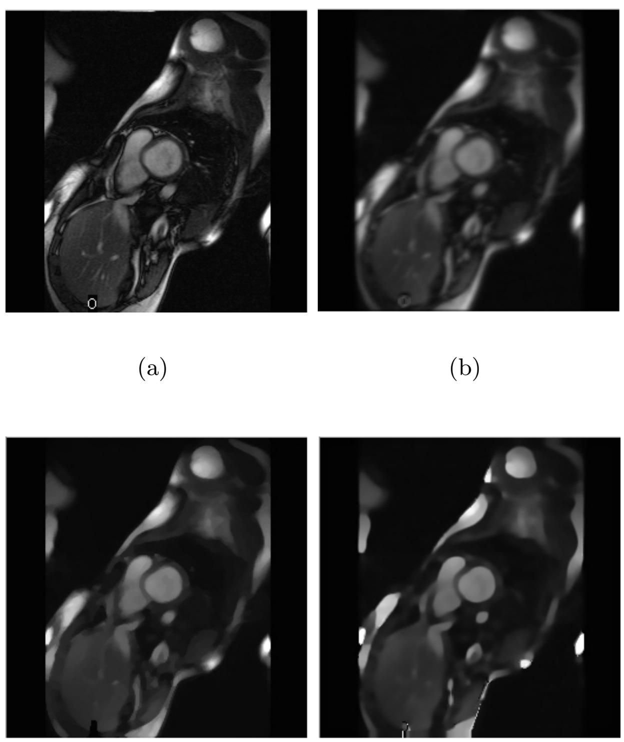
$$I^{t+1}_{xy} = I^t_{xy} + \eta_{xy} \frac{\Sigma_{(i,j)\in N_{xy}(1)/\{(x,y)\}} \eta_{ij} \gamma^t_{ij} (I^t_{i,j} - I^t_{x,y})}{\Sigma_{(i,j)\in N_{xy}(1)/\{(x,y)\}} \eta_{ij} \gamma^t_{ij}} \tag{9}$$

where,

$$\eta_{ij} = \exp(-\alpha\Phi(\tilde{\sigma}^2_{xy}(R), \theta_\sigma)), \tag{10}$$

$$\gamma^t_{ij} = \exp(-E^t_{ij}/S) \tag{11}$$

The variables S and α determine to what extent the local and contextual disontinuities should be preserved during smoothing. If there are a lot of contextual discontinuities in the image then the value of η_{ij} will have a large influence on the updated intensity value. On the other hand, if there are a lot of local discontinuities then both γ_{ij} and η_{ij} will have the overriding effect, as η_{ij} is used for gain control of the adaption.



(a) (b)

(c) (d)

Figure 3: Figures show the filtering of the short axis view *(a)*The original image of the short axis view *(b)*Results after a single pass of a 5x5 average filter, *(c)* Shows the results after a single pass of a 5x5 fifth-largest median filter and *(d)* The results from the Adaptive filtering using a 5x5 neighbourhood mask, note the features edges are best preserved.

4 Clustering

The regions of the 2D image are segmented using the k-means algorithm proposed by Duda and Hart [Duda and Hart, 1973]. This algorithm has four steps to find the image clusters.

(i) Initialise the position of the means $m_1 \rightarrow m_k$.

(ii) Assign each of the k-items to the cluster whose mean is nearest.

(iii) Recalculate the mean for the cluster gaining the new item and the mean for the cluster loosing the same item. Recalculation is made using the variance.

(iv) Loop through steps *(ii)* and *(iii)* until there are no movements of items.

The number of clusters is image dependent so the initial guess is about 15-20 clusters, this number is sufficient to capture all of the relevant clusters. The number of clusters is optimised by merging the clusters with similar attributes. In other words, two adjacent clusters are merged if the difference of their centre values is lower than a preset threshold. This is repeated until there are no clusters to be merged.

4.1 Connecting Regions in 3D

Once the images have being clustered and labeled, the next step is to link all the labels to extract the volume of the left ventricle. The user clicks on the left ventricle label on both the systolic and diastolic images. The program connects the label in the first image to the corresponding label in the preceding image using two criteria;

(i) Overlapping area of the regions contained in successive slices.

(ii) GrayScale value of the regions under investigation

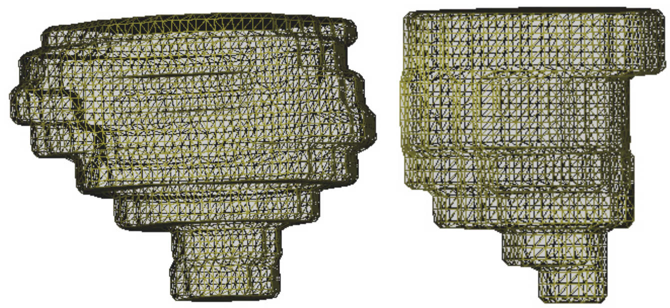
The corresponding region is found by maximising the result of a cost function where the overlapping and the mean grayscale value of the areas under investigation are used as parameters. The rendered images of the systolic and diastolic phases can be seen in Figure 4.

5 Experiments and Results

The Dicom images [1] were 256 x 256, 8 slice and ECG-gated at both the systolic and diastolic phases. For the adaptive smoothing $N_{xy}(R)$ was set to be a 5x5 kernel, the variables α, θ_σ and S were experimentally found to produce best results at 10.0, 0.2 and 14.0 respectfully and run for three iterations. The clustering upper and lower thresholds were also experimetally determined to be 0.65 and 1.35.

The sums of the pixels in the rendered images were integrated to give an Ejection Fraction of 54% for the given data set. The evaluation of the ejection fraction was taken from the definition to be the amount of blood in the left ventricle. The papillary muscles and any endo-cardium fat are not included in the calculation of the ejection fraction. The inclusion of these artifacts was facilitated by approximating the area cross-section of the LV to be a circle. The circles radii were set to the maximum euclidean distance from the centroid of the LV region to the endo-cardium border.

[1] Supplied by Rob J. van der Geest, M.Sc., Division of Image Processing,Department of Radiology, 1-C2S, Leiden University Medical Center



(a) (b)

Figure 4: The figures show the rendered images of the *(a)*Diastolic and the *(b)*Systolic phases of the cardiac cycle. These volumes that are constructed from the true segmentation of the images excluding fat and papillary muscles on the endo-cardium.

With the circle approximation the Ejection fraction for the same sequence is calculated at 57%. This is comparable to Geest's MASS software [van. der. Geest, 2002] which computed the ejection fraction for the same sequence to be 62%. The differences arise from Geest's use of Active Appearance Motion Models (AAMM's) which approximate the shape of the LV but not necessarily with a circle. AAMM's use a priori knowledge about the shape of the left ventricle obtained from a training procedure. A convex hull is drawn around the blood pool which includes the papillary muscles and fat on the endo-cardium. This convex hull is then used in the calculation of the ejection fraction.

6 Conclusion

The proposed algorithm consists of three main parts. The images are smoothed using an adaptive smoothing technique, retaining the important edge information. The segmentation is achieved by clustering the smoothed images. Finally the regions of interest in all slices are joined together and the ejection fraction calculated.

The results are comparable with the Active Appearance Models [B.P.F. Lelieveldt, 2001] and Gradient Vector Flow based snake [M. Santarelli, 2003]. The algorithm is unsupervised and robust against changes in scale, grayscale values and left ventricle pathologies that effect the shape. This is still a work in progress and the next step should be the validation of the work to date with more data sets and manual segmentation by a specialist.

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