Automated Detection of the Left Ventricle Contour in Gated Blood Pool Studies

Luiz Cláudio Parzianello Sérgio Shiguemi Furuie Lincoln Moura

InCor - São Paulo Heart Institute - HCFMUSP - SP&D Divisão de Informática Av.Dr.Enéas de Carvalho Aguiar, 44, 05403.000 São Paulo, SP, Brazil parzianello@incor.usp.br

Abstract. We present a method for automatic detection of left ventricle (LV) contour in gated blood pool studies based on $\nabla^2 G$ operator, used as an enhancing filter. The LV is localized automatically in the diastolic frame using a fuzzy membership function of localization over the filtered image. After that, the LV contour is searched by a region growing algorithm with constraints in the diastolic frame. In the other frames, contours are detected via heuristic local search using the previously detected contour as a template and looking for an optimal path.

Keywords: Image Processing, Medical Imaging.

1 Introduction

The radionuclide ventriculography (gated blood pool - GBP) is an exam intended to evaluate cardiac ventricular function through the acquisition of a scintigraphic image sequence synchronized with the patient's electrocardiogram. Assessment of the left ventricle function is very important as it determines treatment and prognostic. GBP allows the quantitative analysis of cardiac function and permits the determination of the ejection fraction, a parameter that rates overall cardiac performance.

Some hospitals can have more than 120 patients a month to be assessed via GBP study. Usually, in clinical routine, LV function analysis is done by manual drawing of the ventricle contour in both diastolic and systolic frames. On the other hand, fully automated processes for the extraction of the LV contour in routine scans have been described by many authors in the last decades. An abundant literature exists on this subject concerning either automatic or semiautomatic algorithms. For example, whereas some methods work with the synthesis of the first and second derivative images [Hawmann (1981), Lie et al. (1981), Goris et al. (1981)], others use the thresholding operation [Bunke et al. (1982)] or even a mixing of these two methods [Chang et al. (1980)]. There are methods that are based on the choice of a point of the LV as the center of an angular profile network on which an edge enhancement linear operator is applied [Todd-Prokropek et al. (1981)] or as the origin of a polar coordinate-transform where a local edge operator is applied [Niemann et al. (1985)]. Currently, sophisticated probabilistic models [Barett et al. (1982)], contextual knowledge guiding a search of the LV boundary [Duncan (1984,1987)] and fuzzy clustering [Boudra et al. (1993)] have been used to solve this problem.

We propose, in this paper, an approach for the extraction of the LV contour in gated cardiac studies based on heuristic search on the image filtered by the $\nabla^2 G$ operator. The operator was used as an enhancing filter (in the sense of noise removal and contrast enhancing). That operation was performed on left-anterior oblique image-sequences of 32 frame mode computed images acquired by a gamma camera LEM+ (Siemens) on a Max DELTA system (Micro Vax 3300 processor). The algorithm was implemented using AVS development system on a Sparc10 SUN station.

2 The ∇2G operator

The $\nabla^2 G$ operator is the result of the theory of edge detection presented by Marr and Hildreth [Marr-Hildreth (1980)]. The intensity changes, which occur in a natural image over a wide range of scales, are detected separately at different scales through an appropriate filter for this purpose. That filter was found to be the second

derivative of a Gaussian, and it can be shown that, provided some simple conditions are satisfied, these primary filters will not be orientation-dependent. Thus, Marr and Hildreth showed that the intensity changes at a given scale are best detected by finding the zero values of $\nabla^2 G(x,y)^* I(x,y)$ for image I, where G(x,y) is a two-dimensional Gaussian distribution and ∇^2 is the Laplacian. The method is described below.

In order to reduce the range of scales over which intensity changes take place (noise removal), we can use a filter that presents a smooth spectrum and is roughly band-limited in the frequency domain. The filter should also be smooth and localized in the spatial domain, and, in particular, its spatial range should also be small, because the contributions to each point in the filtered image should arise from a smooth average of nearby points, rather than any kind of average of widely scattered points. These two localization requirements are conflicting and the function that optimizes the relation between space and frequency is the Gaussian [Marr-Hildreth (1980)] that can be expressed by

$$G(r) = k \cdot e^{-\frac{r^2}{2\sigma^2}},$$
 (1)

where k is a normalization term, $r^2=x^2+y^2$ (rotationally symetric) and σ^2 is the variance. So, the smoothed image is obtained by G^*I , where * is the convolution operation.

The intensity changes in G^*I are then characterized by the zero-crossings in the second derivative image. This procedure is done through an orientation-independent differential operator, the Laplacian ∇^2 [Marr-Hildreth (1980)], that results in:

$$\nabla^2(G * I) = \nabla^2 G * I. \tag{2}$$

We can write the operator in the r domain, as in (1)

$$\nabla^2 G(r) = k' \cdot (1 - r^2/\sigma^2) \cdot e^{-\frac{r^2}{2\sigma^2}}$$
 (3)

To get a convolution mask of a zero crossing detector we have to return to the original coordinates x, y and to introduce a multiplicative coefficient c that normalizes the sum of mask elements to unity [Sonka-Hlavac (1993)].

$$\nabla^2 G(x,y) = c \cdot \left[1 - (x^2 + y^2)/\sigma^2\right] e^{-\frac{x^2 + y^2}{2\sigma^2}}$$
. (4)

Figure 1 shows a graphic representation for that operator in the spatial and frequency domains, showing a band-pass filter characteristic. We can see that this operator can be effectively approximated by a difference of two Gaussian functions with substancially different σ - this method is called *Difference of Gaussians*, abbreviated as **DoG** [Marr-Hildreth (1980)].

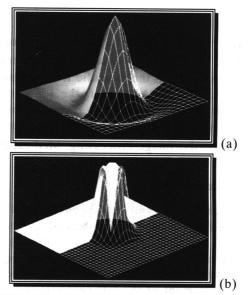


Fig.1. $\nabla^2 G$ in the (a) space domain and (b) frequency domain

If we combine zero-crossing segments from different values of σ (channels) we get what Marr called raw primal sketch, a description constructed with the intensity changes of the image. The Marr-Hildreth's work showed that the minimum number of channels (values of σ) are two, provided that the two channels are reasonably separated in the frequency domain, and their zero-crossings agree. The combined zero-crossings can be taken to indicate the presence of an edge in the image [Marr-Hildreth (1980)].

GBP image is based only on a single physical phenomenon: gamma rays emission. Thus, considering that the objects in radionuclide images are blurred, with the same characteristics in frequency, one channel is sufficient to detect the boundaries between regions of interest. In this case, we have to consider a value of σ comparable with the roll-off of the edge intensities. For good detections, edge roll-off should be equal or smaller than σ [Monteiro (1988)] and a value of 3.0 is a good choice for 64x64 GBP images.

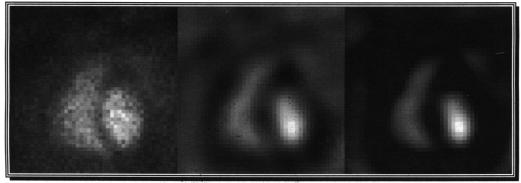


Fig.2. Gated blood pool frame (a) before filtering, (b) after filtering and (c) after clipping

Edges are thus detected by determining the pixels where zero values are crossed in only one channel. Comparing the size of objects, the slope of edges and the size of mask ($\nabla^2 G$) one say that some boundaries can not be detected on close objects where $\nabla^2 G^*I$ in the region will not become zero. So, clipping the negative values to zero and searching for zero values in the neighbour of the regions with values different of zero is another way to localize the edges. Even boundaries not detected via zero crossings can be detected by the valleys (figure 2). The process to localize LV contour in that images will be further explained below.

3 Left ventricle localization

The Niemann's procedure [Niemann et al. (1985)] for finding a point (x_0, y_0) within the LV is based on the heuristics that the LV is always located in the right-hand part of the image and shows higher intensity values than its surrounding region. The problem here is that Niemann did not consider the presence of other structures (spleen, e.g.) in the same side of the image. In some cases, the spleen may have higher intensity than LV. Our purpose here is to use the concept of high intensity values within a region determined by a fuzzy membership function [Zadeh (1965)] of LV center position.

A fuzzy set is a class of objects or points with a continuum of grades of membership where there is no sharp boundary between elements that belong to this class and those that don't [Boudraa et al. (1993)]. Each set is characterized by a membership function which assigns to each point a membership grade in the interval [0,1].

The fuzzy membership function awas estimated by a symmetric two-dimensional Gaussian distribution whose mean and standard

deviation were calculated over 107 gated blood pool exams with a 64x64 resolution. An operator was asked to point at the LV center in each exam. After that, considering x and y as two independent random variables associated to the center position, we got both mean and standard deviation of each variable (\bar{x} =39.5, \bar{y} =36.9, σ_x =2.0, σ_y =2.7). To get a symmetric Gaussian that contains 99.74% of events we used 3 times the highest σ (σ_y) generating the fuzzy membership function (ψ) as

$$\psi(x,y) = e^{-\frac{(x-39.5)^2 + (y-36.9)^2}{2.(8.1)^2}}.$$
 (5)

ψ represents the membership weight of a pixel belonging to the LV in a 64x64 gated blood pool frame in that location. Now, we can look for a maximum in the image resulted from $\psi(x,y).[\nabla^2 G(x,y) * I(x,y)].$ This maximum corresponds to a pixel with the highest possibility of belonging to the LV, not necessarily in the center of it (figure 3). Finally, the center of LV can be roughly located by applying an iterative search for the local maximum in the original image. This assumption is reasonable as in a normal LV the highest intensity is near the LV center.

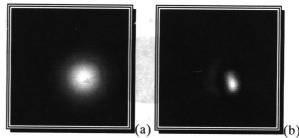


Fig.3. Fuzzy membership function of LV center position (a) and the result applied to the filtered image (2c) (b)

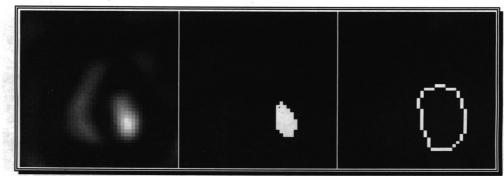


Fig. 5. The starting region (b) is obtained through region growing on the original image (a) around LV center.

The final contour (c) is obtained through region growing with constraints.

4 Diastolic contour detection

The next step is to determine the LV boundaries in the first frame (diastole) of the cardiac cycle. The concept here is to get a start region within the LV boundaries and grow it up until the final boundaries in the filtered image are found. The starting region is obtained through a region growing technique where the homogeneity criterion is pixel value higher than 65% (empiric value) of the LV center pixel value (last step).

The region thus found is further processed by performing another region growing step, this time searching only pixels that lie on a line that is perpendicular to the boundaries of the region at each iteration (figure 4). The initial threshold level is 65% of the LV center pixel level and is decreased at each iteration until becoming zero. The region grows if the pixel value in study is equal to the current threshold and smaller than the previous pixel. The concept underlying this reasoning is that the LV has a smooth contour and that the final boundary matches is likely to match either the zero values or the valleys around the LV contour in the filtered image. Therefore, in each iteration we have to verify if the next pixel is zero or belongs to a valley. If one of these conditions is true growth is aborted in that direction, otherwise it continues.

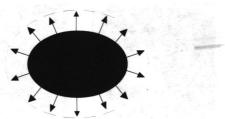


Fig.4. Growth is perpendicular to the object boundaries.

Once finished in all directions we can get the LV contour by determining the inner region border through an *inner boundary tracing algorithm* [Sonka-Hlavac (1993)].

5 Non-diastolic contour detection

With adequate temporal sampling, the LV contour will not change drastically from frame to frame. That is, the wall movement of the heart is much smaller than 1 pixel/frame, considering 32 frames/cardiac cycle. Thus, we can use this information as a template for the search of the next contour.

Assuming that the LV contour varies at most one pixel from the previous contour (high temporal resolution and low spatial resolution) we can create a region with a width of 3 pixels (one inside and the other outside the contour) that represents a possible range containing the next contour (figure 6).

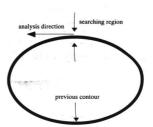


Fig. 6. Region for searching a non-diastolic contour through a local search.

Finding each new LV contour is achieved by firstly finding a starting point within the 3-pixel wide region and then follow the contour by local features, such as zero value pixel with a non-zero neighbor. We can guarantee the singularity (closed contour) by the 3 pixels width path.

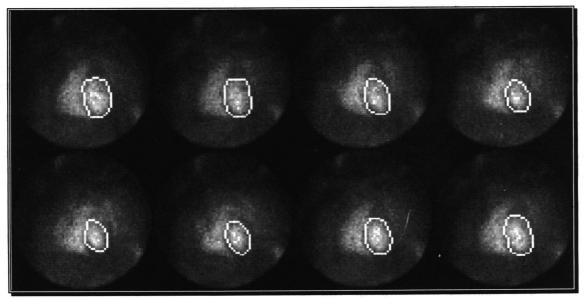


Fig.7. LV contours superimposed onto eight of 32 frames of the cardiac cycle.

Because GBP study is a closed loop, that is, the last frame can be connected to the first, the LV contour in the diastolic frame can be reprocessed by this procedure. The reason for doing this is that, from diastole to systole, the LV contour can be corrected if small problem ocurrs in the last step (region growing) and so the last frame could have a better contour than the first frame.

6 Results and Discussions

The use of $\nabla^2 G$ as a contrast enhancing filter with noise removal showed to be powerful in nuclear medicine images, with some constraints. That is, the size of objects and the slope of their boundaries are important to determine the value of σ . We estimated $\sigma=3$ as a good value for commom cases in GBP studies with 64x64 resolution.

In some cases, the zero-crossing can underestimate the LV size and an object dilation in gray scale (local maximum) after filtering showed to be a good solution because it does not overlap regions in smoothed images and remove small fluctuations. A small overestimation of the LV size in the posterolateral region is permitted here.

A mask with 19x19 elements is necessary for σ =3 for spatial filtering with $\nabla^2 G$. A convolution through Fourier domain by FFT algorithm can

speed up the computation of 32 frames in a factor of 11.

The use of fuzzy sets definition to localize LV region showed to be straightforward and robust, considering only one object feature: spatial location. The fuzzy membership function did not make mistakes about LV localization in the 107 studies. It was expected because the statistical analysis showed a small standard deviation over the mean of LV center in both directions. Since the method proposed is intended to estimate automatically the parameters of systemic circulation in GBP studies, in only one case this assumption will fail: in a congenital case where great vessels are transposed. In this case, the parameters of systemic circulation must be calculated over the right ventricle cavity and the method will not work. We have to point out that it is an exceptional case.

In studies with good labeling of red cells, the LV contour determination through a search of zero-crossings or valleys by region growing on the clipped $\nabla^2 G^*I$ was considered well-defined by the physicians (visual analysis - figure 7). The ejection fraction can be a good parameter for a quantitative analysis of the correlation between automatic and semi-automatic methods for LV function analysis. The problem with this procedure is that the estimation of LV volume (ejection fraction) is dependent on background noise and an automatic algorithm to remove the background noise has to be applied. So, a poor

estimation of the background noise can result in a poor estimation of the ejection fraction even Division of the RR interval into at least 16 frames per cycle (<50 msec/frame) provides adequate temporal resolution for clinical evaluation of regional wall motion and ejection fraction at rest (heart rate of 80) [Rocco et al. (1989)]. For exercise studies data should be recorded with shorter intervals (<25 msec/frame). considering 1 pixel/frame the maximum velocity of the LV wall in 32 frame study is more than the real value and using the previous contour as a template for the next one is reasonable. This technique also showed to be convenient because small problems with diastolic contour detection can be improved in the process, when it reaches again the diastolic phase.

Problems with stannous pyrophosphate (for in vivo labeling) or severely ill patients become difficult to get good labelling of red cells. The result is an image with poor or no contrast between cardiac cavities and presence of other structures near LV. In this case, the method can take a piece of the right ventricle as belonging to the LV or reject an aneurysm from the LV area. To solve this problems, we are working in a new procedure that expect such pathologies in the diastolic frame. The process uses the watershed algorithm for the region growing and permits more than only one region for the LV. So, a labeling step has to be incorporated to the algorithm after segmentation.

7 Conclusions

We presented a technique for the automatic detection of the LV contour in GBP studies. The method makes use of the V2G operator not as proposed by Marr-Hildreth but as an enhancing filter. The localization and boundaries detection are based on heuristics of the LV behavior in normal clinical procedures of GBP studies. We applied the proposed technique on a set of images with good results in most cases. The method showed to be robust even in images with poor contrast and high noise level with a better performance than most methods proposed in the past. The main advantages of automatic methods is that they speed up diagnostic procedures and are repeatable, thus eliminating inter-operator variability. The proposed method allows the computation of LV performance, including ejection fraction and wall movement with little operator intervention.

though the LV contour is detected correctly.

References

W.A.Barett et al. "High-Speed processing of digital intravenous angiocardiographic images for enhancement of coronary bypass grafts and quantitation of left ventricular function", Computers in Cardiology, (1982), 101-104.

A.E.O.Boudraa et al. "Left Ventricule Automated Detection Method in Gated Isotopic Ventriculography Using Fuzzy Clustering". IEEE Trans Med Imaging., v.12, n.3 (1993), 451-465.

H.Bunke et al. "Smoothing, thresholding and contour extraction in images from gated blood pool studies", in *Proc. 1st IEEE Comput. Soc. Int. Med. Imaging and Image Interpretation*, Berlin, West Germany (1982), 146-151.

W.Chang et al. "Methods for detection of the left ventricular edges", Seminars in Nuclear Medicine, v.X (1980), 39-53.

S.M.Collins, D.J.Skorton, Cardiac Imaging and Imaging Processing, McGraw-Hill, New York, 1986.

J.S.Duncan. "Intelligent determination of the left ventricular boundaries in gated nuclear medicine image sequences", in *Proc. 7th Int. Conf. Pattern Recog.* (1984), 875-877.

J.S.Duncan. "Knowledge direct left ventricular boundary detection in equilibrium radionuclide angiocardiography", *IEEE Trans. Med. Imaging*, v.6 (1987), 325-336.

M.L.Goris, et al. "A fully automated determination of the left ventricular region of interest in nuclear angiocardiography", Cardiovascular Int. Radiol., v.4 (1981), 117-123.

E.G.Hawmann, "Digital boundary detection techniques for the analysis of gated cardiac scintigrams", *Opt. Eng.*, v.20, n.5 (1981), 719-725.

S.P.Lie, et al. "A fully automated determination of the left ventricular region of interest in nuclear angiocardiography", Cardiovascular Int. Radiology, v.4 (1981), 117-123.

D.Marr, E.Hildreth. "Theory of Edge Detection", *Proc. Royal Soc. London*, B207 (1980), 187-217.

A.M.V.Monteiro. Processamento de Imagens de Satélite Usando Estruturas Simbólicas do Baixo Nível da Visão. M.Sc. thesis. Instituto de Pesquisas Espaciais, São José dos Campos, 1988. 103pp.

H.Niemann et al. "A knowledge based system for the analysis of gated blood pool studies", *IEEE* Trans. Patt. Anal. Machine Intell., v.PAMI-7 (1985), 246-258.

M.Sonka, V.Hlavac. Image Processing, Analysis and Machine Vision. Chapman & Hall Computing, London, 1993.

T.P.Rocco *et al.* "Evaluation of Ventricular Function in Patients with Coronary Artery Disease". The Journal of Nuclear Medicine, v.30, n.7 (1989). 1149-1165.

A.Todd-Prokropek *et al.* "Edge detection: an intercomparison of different algorithms", in *Proc.* 7th Int. Meeting IPMI, M.L.Goris ed. (1981), 329-341.

L.Zadeh. "Fuzzy Sets". Information and Control, n.8 (1965), 338-353.