Abstract - In this work a comparative study of some methods of Left Ventricle segmentation in echocardiographic images is developed. The project is developed in four modules denominated: Acquisition, Segmentation, 3D Reconstruction, and VRML Visualization. 1) The images acquisition of volume sequences of the left ventricle was obtained during an echocardiographic test. This allows the acquisition of 60 sliced planes in a rotational 3D symmetry. 2) Three segmentation methods were developed adapted to the characteristics of the images: a) Active contour models "Snakes" based on the energy-minimizing of a spline. b) Models with front propagation based on Sethian's ideas for a closed curve. c) A third model that combines the 3D acquisition geometry of a volumetric sequence with the superquadric deformable model. This global model has the capacity to segment and to capture the global parameters of size, shape and orientation required by doctors for the analysis of heart dynamics. 3) It realized the 3D Reconstruction and visualization taking advantage of the cylindrical geometry from the images acquisition. In conclusion, the obtained results are consistent with the apparent motion pattern observed of the left ventricle. The doctors can able to visualize and to detect the pathologies better; for example: ischaemia or heart attack observing the dynamics of the developed model.

I. Introduction

A WorkStation was developed to acquire, reconstruct, process, and visualize 4D images of the heart, from two-dimensional echocardiography equipments, using the method of transtoracic rotational swept. The description of the problems and the solutions, associated to the acquisition of the 3D dynamic images of an organ in movement are documented in previous works realized by the authors [1].

With the purpose of studying the movement of the heart, the calculation of ejection volume, and the reconstruction and visualization 3D and 4D images of the left ventricle, is necessary to previously realize a segmentation of the left ventricle to each one of the images of the space-temporal sequence. The segmentation can be manual, computer aided, or totally automatic. The manual segmentation requires a considerable time on the cardiologist, more when the sequences are larger. For example, the quantity of 2D images to be segmented varies between 900 and 1800 for a single clinical exam. The objective of this work is to provide to the doctor an useful tool for the analysis of the 3D echocardiographic images and 3D visualization. We have developed three methods of segmentation based on the search of a local minimum of energy, or minimizing a cost function. These methods are: a) Active contour models "Snakes" b) Models with front propagation based on Sethian's ideas for a closed curve; and c) A third model that combines the 3D acquisition geometry of a volumetric sequence with a superquadric deformable model.

2.1. Active contour models “Snakes”.

A snake is an spline which behavior is based on the energy-minimizing physical theories. The spline is guided by external forces and influenced by internal forces of the image with the purpose of detecting the borders or contours of a shape within an image. The snake provides an unique environment which allows the solution of several visual problems, such as: edge detection, lines detection, subjective contours, and motion tracking.

Kass et al. [2] investigated the energy-minimizing functions and their application, on detection of images contours, lines detection, and subjective contours. They developed some energy functions that converge to a local minimum dependent of the initialization. The main objective is to detect in an interactive and exact manner, the contour of an object, on situations when traditional techniques based on the pixels vicinity, threshold, etc. give false contours as a result. Frequently the segmentation of images using deformable models, adapts the different morphologies and anatomical structures of the human body. Therefore, the snakes constitutes a promising solution to this problem, allowing the segmentation and modelization at the same time [3][4].

The utility of the snakes is its capacity to segment and to follow the anatomical structures inside a given image, exploiting the knowledge a priori of size and shape of the structures. These models allow the doctor's intervention who can include their experience applied to the images interpretation.

2.1.1. Model Bases:

The deformable models are based on theoretical foundations given mainly by geometry and physics. The geometry imposes the form of the object to detect, and the physics determines the conditions of elasticity, temporary
deformations, space deformations, and the internal and external forces applied to the model. We should add the approach theory which will allow us to realize the convergence of the model using functions of minimum cost based on the internal and external forces of the image.

The internal forces of the spline represent the elasticity and rigidity of the curve. They are good to impose a soft form to the curve and to assure their continuity. The external forces pushes the snake toward features of the image, such as: lines, borders, etc. These forces are sometimes placed in an interactive way with the user with the purpose of guiding the snake toward the structures of interest.

### 2.1.2. Basic behavior of the Snake.

A snake can be represented in a parametric form as following:

\[ V : \Omega = [a, b] \rightarrow \mathbb{R}^2 \]
\[ s \rightarrow \mathbf{v}(s) = (x(s), y(s)) \]

(1)

It can write the energy function \( E \) of the snake as:

\[ E_{\text{snake}}(\mathbf{v}) = \int_a^b E_{\text{int}}(\mathbf{v}(s)) + E_{\text{ext}}(\mathbf{v}(s)) \, ds \]

(2)

where: \( E_{\text{int}}(\mathbf{v}(s)) \) is the internal energy of the spline caused by the deformations, and \( E_{\text{ext}}(\mathbf{v}(s)) \) is the energy of the external forces applied to the snake on the point \( \mathbf{v}(s) \).

The internal forces determine the regularity of the snake. Therefore, it is possible to obtain flat contours on a very noisy image. The internal energy of the spline can be expressed as:

\[ E_{\text{int}}(\mathbf{v}(s)) = \alpha(s) \left| \frac{\partial \mathbf{v}(s)}{\partial s} \right|^2 + \beta(s) \left| \frac{\partial^2 \mathbf{v}(s)}{\partial^2 s} \right|^2 \]

(3)

where: the first term represents the stretching or elongation and the second term the bend of the “snake” at the point \( \mathbf{v}(s) \). The coefficients \( \alpha(s) \) and \( \beta(s) \) control the relative contribution of two internal energies at the point \( \mathbf{v}(s) \).

The last term \( E_{\text{ext}}(\mathbf{v}(s)) \) is the external energy used to take the “snake” toward the desired contour. This make up of an energy calculated from the image and a potential energy placed by the user:

\[ E_{\text{ext}}(\mathbf{v}(s)) = \omega_i E_{\text{image}}(\mathbf{v}(s)) + \omega_o E_{\text{user}}(\mathbf{v}(s)) \]

(4)

Where: \( \omega_i \) and \( \omega_o \) are the weighted contribution of the external energy. The image energy is a potential energy:

\[ E_{\text{image}}(\mathbf{v}(s)) = P(\mathbf{v}(s)) \]

(5)

In the simplest case, the potential energy is placed as the negative of the intensity of the image. However to obtain better results, the gradient is used, since it is known that the areas of strong gradient generate a potential field that attracts the dynamic contour. If the areas of strong gradient are punctual, the contour dynamic initial must be positioned very near the contour to be detected. Kass et al. [2] proposed a potential energy calculated as following:

\[ P(\mathbf{v}(s)) = -(G_{\sigma} \ast \nabla I(\mathbf{v}(s)))^2 \]

A snake should be initialized in the vicinities of the region of interest, so it can be deformed toward a minimum of local energy. The user can intervene to realize modifications and to improve the approach. When the result segmentation is a satisfactory, the same parameters can be used to segment the rest of images sequence in an automatic way.

### 2.2. Models with front propagation.

The shape modeling is important to the computer vision. Shape models aid the tasks of object representation and recognition. Malladi, Sethian et al. [5] developed a propagation model of a closed curve, nonintersecting, hypersurface with a constant speed or a speed that depends on the curvature. The basic curve begins to grow inside the image adapting and sticking to the walls of the structure or object to search. This technique can be applied with the purpose of looking for arbitrary shapes, which also include significant protuberances, and situations when an object’s topology assumption cannot be realized a priori.

Kass et al. [2] realized works of contours and borders extraction using snakes and minimization of energy. However, the snakes was always dependent the initial shape. In this section a new technique is presented which solves this problem. Now shapes could be more complex and with protuberances.

#### 2.2.1. Shape Recovery:

The main idea is to extract objects, shapes from a given image. The front propagation should be forced to stop in the vicinity of the borders of desired objects. This is made synthesizing the speed term in a given image, placing a stop criterion. Two forces exist, a force that inflates the form called \( F_A \), and a \( F_G \) force that depends on the geometry of the propagation front, that is to say, the local curvature. The total force is: \( F = F_A + F_G \).

#### 2.2.2. Simplified algorithm.

A smooth, continuous, derivable, closed and euclidean curve \( \gamma(0) \) is defined in \( \mathbb{R}^2 \). It sub-sampling the points of the continuous curve in “N” discreet values. The front propagation is initialized considering that the vectorial addition of all the expansion forces to the center of masses of the object to detect is 0. The speed of the front propagation is directly proportional to a variable \( k_1(x,y) \) defined by Malladi, Sethian et al. [5] as:
\[ k_i(x,y) = \frac{1}{1 + \| \nabla G \|^2 * I(x,y)} \] (7)

In regions with a high gradient the variable \( k_i(x,y) \) approaches to a near value of zero. While the regions with relatively constant intensity, the gradient approach to zero and the variable \( k_i(x,y) \) approach to “1”. This is one of the stop criterions used by Sethian [5].

Algorithm.
1) At each grid point \((i\Delta x, j\Delta y)\). Where \( \Delta x \) and \( \Delta y \) are the step sizes in any address. The extension term of speed is calculated based on the image.
2) With the value of extended speed term \( (k_{i,j})^{n+1} \) and \( \psi_{i,j}^{n} \), is calculated \( \psi_{i,j}^{n+1} \) that corresponds \( n+1 \) of a new curve. Finite difference schemes are used to calculate.
3) It builds an approximation for the level set from \( \psi_{i,j}^{n+1} \). The new forces are calculated as:
\[ F_{new}(i,j) = k(i,j)A(i,j) + F_{c}(i,j). \]

They are carried out some approaches, and the new level set is obtained \( \psi_{i,j}^{n+1} \).
4) To replace “N” by “N+1” and return to step 1.

2.3. Deformable model: Superquadric.

The superquadrics (figure 1) are a family of parametric curves that were used by Terzopoulos and Metaxas [6] to model a complex 3D shapes. They formulate deformable superquadrics which incorporate the global shape parameters of a conventional super-ellipsoid. A superquadric surface is the spherical product of two superquadric curves and can be defined in a 3D vector form as follows:
\[
S(\theta, \phi) = \begin{bmatrix} x \\ y \\ z \\ \end{bmatrix} = \begin{bmatrix} a \cos^e(\theta) \cos^e(\phi) \\ b \cos^e(\theta) \sin^e(\phi) \\ c \sin^e(\phi) \\ \end{bmatrix}
\] (8)

Where the parameters \( \theta \) and \( \phi \) are between: \(-\frac{\pi}{2} \leq \theta \leq \frac{\pi}{2}\) and \(-\pi \leq \phi \leq \pi\). \( \theta \) and \( \phi \) correspond to latitude and longitude angles, respectively, expressed in a spherical coordinate system. The values \( a, b \) and \( c \) define the size of the superquadric in the coordinate \( x, y \) and \( z \) respectively. The exponents \( e \) are the squareness parameters along the z-axis, and the x-y plane, respectively.

The implicit equation of the superquadric-one can be obtained evaluating the following equation:
\[
\left[ \left( \frac{x}{a} \right)^2 + \left( \frac{y}{b} \right)^2 \right]^{\frac{1}{e_1}} + \left( \frac{z}{c} \right)^{e_1} = 1 \] (9)

2.3.1. Minimization Algorithm.

The energy of the error is minimized when the parameters of this model are adjusted using a similar focus to the training of the Back Propagation neural network.

It was defined as objective function the minimization of the following error expression:
\[
err = \sum_{a_i, p_n} \left[ 1 - F(p_n, a_i) \right]^2
\] (10)

where:
- \( F(p_n, a_i) \) is the implicit equation of the superquadric (equation 9) with all transformations.
- \( p_n \): are the points coming from the segmentation of the ventricle
- \( a_i \): are the parameters of the deformable model.

The function \( F(p_n, a_i) \) takes the following values:
\[
\begin{align*}
F(p_n, a_i) &= 1 & \text{If } p_n \text{ is on the superquadric surface.} \\
F(p_n, a_i) &= 1 \quad & \text{If } p_n \text{ is outside of the superquadric.} \\
F(p_n, a_i) &< 1 & \text{If } p_n \text{ is inside of the superquadric.}
\end{align*}
\]

The vectorial gradient of the error function (\( \nabla err \)) indicates the direction of the growth of the objective function, consequently the parameters \( \dot{a}_i \) are modified in small increments in opposed direction.

3. Results.

Next results of the 2D processing are shown using edges detection with deformable snakes, (Figures 2). It can observe in these results the internal wall detection of the left ventricle. In this case the original images are filtered and they hardly have noise speckle. In the figure 3a, We can see the image segmented with the method of growth of regions based on the statistics of first and second order of the image, it can appreciate a significant error in the superior part of the image, since there is a loss of section when the acquisition echocardiographic image is carried out.

![Figure 1. Superquadric, (ellipsoidal).](image_url)

This work carried out a comparative study of three segmentation methods of images applied to detection of the left ventricle in echocardiography. The first method using "snakes" shows better results than the growth of regions (figure 3a) based on the local statistics of mean and variance. The first method minimizes the energy of a spline influenced by internal and external forces to obtain a soft shape nearest to the actual structure of the left ventricle (figure 3b). The segmentation using the front propagation model works with a minimum interactive intervention of the Doctor who places the mouse inside the structure to detect (figure 4a). Notice a small circle, it will begin to grow until sticking to the walls of the left ventricle, with the advantage that can be initialized at any point of the interior and it works better than the snakes method that should be initialized in a near region to the walls of the left ventricle to obtain the energy minimization. The last method using deformable superquadrics is still development and it can segment and model the left ventricle taking advantage from 3D cylindrical geometry used to the acquisition and the 3D superquadric shape (figure 5 a,b). The Doctors will be able to carry out a better diagnosis if they can see more clearly images, with different points of view, and many arbitrary observation angles that alone can be obtained after carrying out the 3D reconstruction. For this reason, if the segmentation of medical images is better; the 3D reconstruction will improve.

Bibliography


