Fusion of a Priori Model for the 3D Segmentation of the Left Ventricule in Echocardiographics Images

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Abstract

This paper proposes a new segmentation method for the echocardiogaphic images based on data fusion theory. This proposal consists on a data fusion system with two inputs: The "A" input corresponds to the gradient image after having made the pre-processing links to the acquisition, filtering and interpolation. The "B" input corresponds a parametric equation of a priori model whose equation can be an ellipsoid or a superquadrics. These two inputs are fusion together by using the Bayesian methodology of probabilities with the purpose to obtain a new function "F". That will be used to stop the Level Set Method to segment the inside of the internal wall of the Left Ventricle (LV). Finally the 3D visualization of the LV volume is obtained using the method of marching cubes, and the 3D global model is adjusted to the previous reconstruction. The analysis of the Mean Square Error (MSE) between the calculated model and the real LV volume is smaller than 5%, which confirms the precision of computing of the global medical parameters. In conclusion, the segmentation method based on data fusion allows to obtain simultaneously the global model and the local model of deformation.

1. Introduction

Making a segmentation of echocardiographics images is a complex problem. Frequently, the echocardiographic image shows a loss of regions, as consequence of the physical principle of the acquisition system and the geometric configuration used. The speckle noise, characteristic of the echocardiographics images is also important. Other complications, such as low resolution and low contrasts, make that the extracted information of the image gradient to be insufficient to segment the image.

As a consequence of these troubles with echocardiographics' images, we should find a way of combining the information coming from the gradient of the image with some a priori information, to thus complete the areas where there are losses of regions. The cardiologist makes a mental reconstruction combining the information a priori, coming from his anatomy knowledge, with the sequence of ultrasound images. That is the reason why we decided to simulate the a priori knowledge of the physician with a 3D geometric structures that represents the model of the LV or the model of the heart. This model is designed a priori in the initialization of the proposed algorithm. This model's combination with the numeric data is possible due to the existent theories of data fusion.

This work presents a new contribution for the data fusion methodology. This consists of the fusion, of a priori model defined by mathematical equations and the extracted information of the numerical data obtained from an acquisition system [1].

1.1. Fusion analysis for the segmentation

Generally, the data fusion is made from the data acquired by different transducers. However, in our case we have a single transducer that acquires echocardiographics images in a radial cylindrical geometry. Therefore, the fusion was made among a 3D model that can be considered a priori, and the information obtained with the transducer.

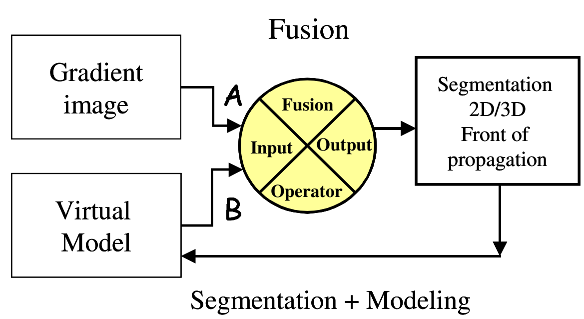

Figure 1. The proposed fusion schema.

The fusion scheme that we propose is described in the figure 1. It is based on the fusion of a virtual mathematical model and the information obtained from our acquisition system. The fusion system designed by the symbol ⊗ possesses two inputs: Input ***"A"*** corresponds to the image of the gradient after having done the pre-processing related to the acquisition and filtering. The input ***"B"*** represented by a parametric equation of a priori model; it has already been studied [2], this equation can be an ellipse or a superquadric.

How can two information inputs of different nature be fusion together?. The image of the gradient gives us the information of the place to stop the propagation front [3]. The other input, the virtual model, is a mathematical function of the ellipse in 2D and the superquadric in 3D, dividing the space in three regions. These two sources of information: the gradient of the image and the distance to the a priori model, have as a common objective to stop the propagation front on the edges of the object that we are looking for. Using the bayesian approach for the data fusion, plus certain conditions, we will be able to find the way to combine these two sources of information of different nature. Next, the deduced components of the data fusion will allow the stopping of the propagation front.

2. Specifications of the components

2.1. Component extracted from the real image

The objective is to detect the edges and the surfaces of a data volume of images. To do this, in [1,3] we developed a segmentation method using propagation fronts whose main equation is the following one:

$$\Psi_t + F(x,y,z)\left|\nabla\Psi(x,y,z,t)\right| = 0 \qquad (1)$$

where Ψ, corresponds to the function of the hyper-surface, Ψ_t is the derived with respect to time, and $\boldsymbol{F}$ represents the speed of propagation of the movement of the curve in the normal direction. The level set zero, described by the function $\Psi(x,y,z,t=0)$ corresponds to the interface that we are looking for. It is the speed function where we will make the data fusion between the gradient of the image and the a priori model. Malladi and Sethian [3] defined a function to stop the propagation front:

$$MR(x,y,z) = \frac{1}{1+\left|\nabla G_\sigma * I(x,y,z)\right|} \qquad (2)$$

where, $I(x,y,z)$ corresponds to the gray level of the image, and the term $\nabla G_\sigma * I$ is the gradient of the gaussian filter applied to the gray level of the original image.

2.2. Component extracted of *a priori* model

A new component, obtained from a three-dimensional object, and represented by an implicit equation, will be used for the data fusion. We aim for a fusion of a parametric model that corresponds to the global deformations with a non-parametric model which corresponds to the local deformations. The general equation of the parametric model is the following one:

$$g(x,y,z) = \left(\frac{x-x_0}{a}\right)^2 + \left(\frac{y-y_0}{b}\right)^2 + \left(\frac{z-z_0}{c}\right)^2 \qquad (3)$$

This implicit equation represents a model that delimits the space in three regions: the interior of the object, the surface, and the exterior. The calculation of the parameters is done considering the moments of first and second order of a cloud of points uniformly distributed in space.

2.3. Basic proposal for the fusion

The objective is to replace the function of speed for the following function:

$$F(x,y,z) = [MR(x,y,z) \otimes MV(x,y,z)](\beta_0 - \beta_1\kappa) \qquad (4)$$

where $MR(x,y,z)$ is given by the equation 2, $\otimes$ is the symbol used for the data fusion and $MV(x,y,z)$ is the relationship of ownership from a voxel to *a priori* model; β_0 is the speed constant of the initialization of the propagation front. β_1 is a constant that controls the mean curvature (κ) of the front surface.

3. Bayesian Approach

Bloch [4] described several operators to make the data fusion and she made a classification into three classes. If we choose the data fusion based on a bayesian probabilistic model, the ownership are represented by the probabilities: *a priori*, conditional and *a posteriori*. Let ***M*** as *a priori* model like (sphere, ellipsoid or superquadric), for example, the equation (3). ***A*** and ***B*** are two sources of information [4], using the theorem of Bayes we obtained:

$$\Pr(M|A,B) = \frac{\Pr(A|M)\Pr(B|M)\Pr(M_0)}{\Pr(A)\Pr(B)} \qquad (5)$$

From this equation, we deduced the used operator, that is the product of two probabilities. The term $\Pr(A)\Pr(B)$ is a normalization term, which is constant for all events.

3.1. Calculation of the probability $\Pr(A|M)$ from the numeric data

The stop function depends on the image gradient and it is given by the probability to compute in each voxel of 3D volume the following function:

$$\Pr(A(x,y,z)|M) = \frac{1}{1+\left|\nabla G_\sigma * I(x,y,z)\right|} \qquad (6)$$

A probability $\Pr(A|M)$ is built starting from the term $\nabla G_\sigma * I$ that represents the gradient of a gaussian filter applied to the gray levels of the original image. This is an empiric construction that can be justified mathematically. The equation (6) will give the information of the probability to stop the propagation front on the edges or contours of the object that we are looking for.

3.2. Calculation of the probability $\Pr(B|M)$ from a priori model

Let us a function, for example the equation (3), which allows to calculate the distance of each point from the 3D volume to *a priori* model. While far away is one pixel from the model, the function $g(x, y, z)$ will give a higher value. In consequence, we should find a function of probability $\Pr(B|M)$ approaches zero as the function distance increases. At first approach, we use the equation (7) under the hypothesis that the interior of the object, belongs to the same object. Therefore, we assign a distance equal to zero. Applying these conditions to the equation (3) is obtained:

$$H(x, y, z) = \begin{cases} \text{if} \quad (g(x, y, z) < 1) \text{ then } g(x, y, z) = 0 \\ \text{if} \quad (g(x, y, z) \geq 1) \text{ then } g(x, y, z) = g(x, y, z) \end{cases} \qquad (7)$$

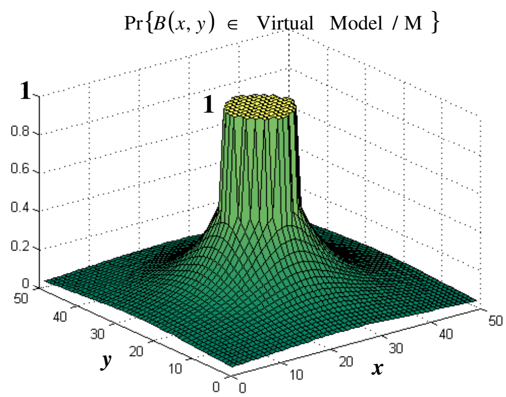

Figure. 2. The probability that each pixel $B(x, y)$ belongs to the virtual model *M*.

This produces a discontinuity in the function $H(x, y, z)$. It is important to find an equation, so the probability of each internal voxel of *a priori* model is equal to one; while the probability of each external voxel is a dependent function of the distance. The front propagation should be spread among the next points to the *a priori* model. We use a probability function for each voxel of the image, similar to the equation (6):

$$\Pr(B(x, y, z)|M) = \frac{1}{1 + H(x, y, z)} \qquad (8)$$

If the distance $H(x, y, z) = 0$, the probability $\Pr(B|M)$ of being inside of the object is equal to one. While, as the distance $H(x, y, z)$ increases, then, the probability of being inside the object will approach zero. The figure 2 shows the function of conditional probability $\Pr(B|M)$. Substituting the equations (6) and (8) in the equation (5), we obtain the probability *a posteriori* of our model.

$$\Pr(M|A, B) = \left[\frac{1}{1 + |\nabla G_\sigma * I(x, y, z)|}\right] \cdot \left[\frac{1}{1 + H(x, y, z)}\right] \Pr(M_0) \qquad (9)$$

$F(x, y, z) = \Pr(M|A, B)(\beta_0 - \beta_1 \kappa)$ represents the new function of speed.

4. Results

The researchers of the Laboratory “d'Electronique, Signaux et Images LESI de l'Université d'Orléans” has developed the VG4D program [5] that allows to reconstruct the volumetric deformations of the left ventricle from echocardiographic images acquired during a heart cycle, with a rotational trans-thoracic transducer. The originality of this electronic sweeping transducer is the implementation of a quick rotation (up to eight times per second) of the piezo-electric sensor around the main axis of the transducer.

The figure 3 shows some echocardiographics images. We observe the acquisition with a very low quality. In these images we observe a low contrasts, losses of regions, and a lot of speckle noise. In consequence, it is very difficult for a classic segmentation method to work well under these extreme conditions.

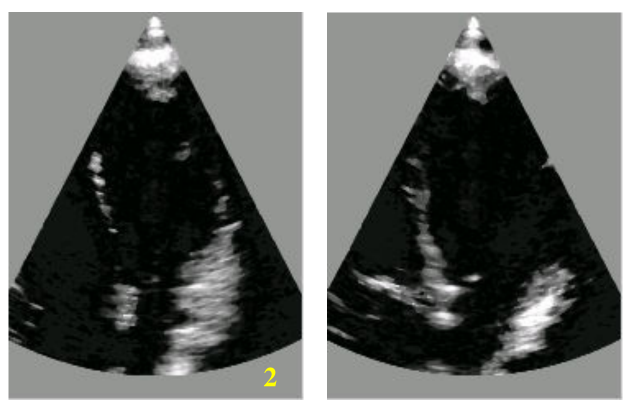

Figure 3. Two echocardiographic slices of the left ventricle corresponding to the rotation planes 2, 4 using the ultrasound transducer.

The images of figure 4, were filtered and we obtained images without noise. However, this information is not enough to introduce the segmentation algorithms, since there are losses of regions that will impede the complete reconstruction of the left ventricle. When the cardiologist makes his medical diagnosis, he doesn't use a single echocardiographic image. The continuous movement of the images, plus the mental fusion of the image with the following one, provides the important information for the medical diagnosis.

In figure 4, we cannot make the segmentation of the echocardiographic images of low quality only using the two-dimensional information and the gradient of the image. Therefore, it is necessary to make an additional process to complete the lost regions. Taking advantage of the radial cylindrical symmetry of these images, the lost edges can be completed using the information of two neighboring images and the data fusion.

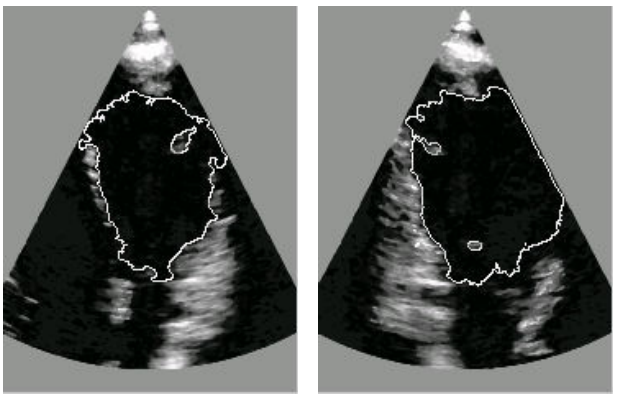

Figure 4. Segmentation of two images using only the "Level Set" method applied to the echocardiographic images.

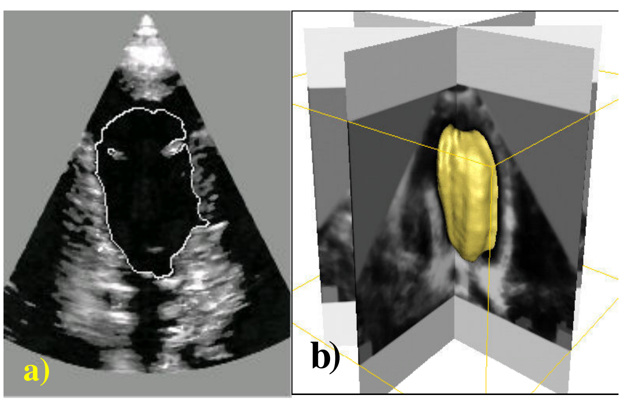

Figure 5. Segmentation using the data fusion method of propagation fronts with an elliptic model. (a) Shows the edge detected. (b) Shows the 3D reconstruction of the LV with a three plans in a radial cylindrical geometry.

We observe a considerable diminution of the losses of regions. However, to stop the front using only the information of the image gradient is not appropriate for the segmentation of echocardiographic images. This is an important reason to have chosen the data fusion with a priori model and to be able to stop the front when there are losses of regions. In the figure 5, we can see the detection of the internal cavity of the left ventricle although the superior part of the image does not exist.

5. Discussion and conclusions

In this work, we developed the following hypothesis: the fusion of a priori model with the extracted information of the image gradient will improve the detection of the LV in the cases of losses of regions like those observed in the superior part of the images of figure 3.

In conclusion, the segmentation method based on data fusion allows to obtain simultaneously the global model and the local model of deformation. That deformation is uniform in a healthy heart. While in the case of infarcts the physician can search the hypo kinetics and akinetics areas. A local model can analyze the ischemic cardiophaties, since it has been demonstrated in the case of infarcts. The necrosis of the myocardium shows anomalies in the ventricular kinetics. On the other hand a global model allows obtaining a certain quantity of global medical parameters, such as: ejection fraction, volume of the LV, cardiac output, all of which allow the making a clinical evaluation on the health of the patient's heart [6].

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