Left Ventricle Tracking in Isotopic Ventriculography Using Statistical Deformable Models

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Abstract: *The left ventricle tracking in planar scintigraphic images is an important step to study the coronary state. However, it is not as simple as we thought, because of the bad quality of these images. The study of the related work showed that classic methods based on low level image characteristics failed to localize the ventricle. In this paper, we suggest using a method based on a priori knowledge. Assuming that the human heart can appear in different images as one of a variety of possible shapes, we can incorporate the shape and the texture to delineate the boundaries of the left ventricle.*

Keywords: *Active shape model, active appearance model, planar nuclear image, tracking, left ventricule.*

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1. Introduction

In nuclear medicine, images are used as an indicator of the functionality of some organs. This discipline admits many diagnostic applications, in particular for the coronary state study named isotopic ventriculography. Compared with other methods of cardiac function investigation, the isotopic ventriculography has an indisputable originality because of its multiple advantages. In fact, it is a physiological and quantitative exploration. Moreover, it offers the possibility to follow the cardiac function. All these advantages, associated to the reliability and the satisfactory reproducibility, make this technique typical to study the ejection fraction ventricular (i.e., quantity of blood ejected during a cycle) [7]. For scintigraphic (or nuclear) images analysis, the simplest approach consists in interpreting visually the images in order to detect hypofixations or hyperfixations revealing of pathology. In addition, it is often desirable to characterize objectively the detected anomalies.

Three analysis methods are then possible: Regions Of Interest (ROI) analysis, parametric imagery and multivariate analysis. In parametric imagery, we follow the activity of each pixel. This ensures the cartography concept conservation. In multivariate analysis, we draw time curves of each pixel. In ROI analyzes, we study the global activity of one or many ROI. The ROI analysis is clearly distinguished because of the difficulty of ROI localization.

In practice, doctors traced manually the ROI what poses a problem of operators' variability [1]. Manual segmentation becomes then a source of errors. Indeed, several studies show that inter and intra variability observers is not negligible. In a study relating to the perfusion index compute of two hemispheres in cerebral scintigraphy, five users traced in six times the ROIs. Results differ of 19 to 43 % [4, 6]. To overcome these drawbacks, development of automatic segmentation methods is necessary. This can insure robustness and diagnosis precision. But, development of such algorithms is not as easy as we could believe.

The present paper focuses on the problem of automatic localization of the Left Ventricle (LV) in scintigraphic images, resulting from an isotopic ventriculography. The proposed method is based on the statistical deformable models. In fact, contrary to classical approaches of contours detection, statistical deformable models incorporate an a priori knowledge on the object shape and anatomy. This knowledge can result from a training set where a reference shape and deformation modes can be extracted.

The paper is organized as follows. In section 1, an overview of proposed methods in LV delineation were presented. For each method, details are presented and discussed. In section 2, we proved the importance of integrating a prior knowledge (about the shape and the texture) in the ventricle localization. Section 3 presents the theoretical background of statistical deformable models and our contribution to the delineation of the left ventricle. An optimisation step is also done to choose the model parameters that provide better results. Results are then evaluated using subjective and objective criteria.

2. Overview of LV Localisation in Scintigraphic Images

In planar scintigraphic images, it is difficult to distinguish ventricle boundaries from neighbouring regions. Even manually, operator is in front of a difficult choice: either to trace great ROI with the risk to merge pixels of different structures, or to trace small ROI with the risk to lose significant information. Contours delimitation is subjective, witch induces inter and intra observers variability.

The nineties beginning recorded the first attempts of scintigraphic images analysis and consequently the first semi-automatic and automatic segmentation methods. Two segmentation approaches were then explored: the based region approach and the based edge approach. The region approach was firstly used by Pladellorens *et al*. [21] who have used mathematical morphology tools to locate the left ventricle. In this approach, results are strongly depending on the method parameters values. Indeed, in addition to its dependence to the threshold values and to the structuring elements size and shape, this method has a major limitation which appears particularly in the systole. In these images, the LVcan not correspond to a local maximum; then it does not seem like a peak but the continuity of the right ventricle.

Other researchers used the region growing method based on histogram analysis [9]. The resulting images are post processed by mathematical morphology operators. The major limitation of this method is that histogram analysis does not allow always regions separation and then the method is sometimes adjusted manually.

In one of our studies, the estimation maximization algorithm was used, an improvement of this algorithm is then proposed using a multi resolution analysis. Although this method presents some interest points, it failed to separate the two ventricles in poorly contrasted images [18].

For based contour approach, second derivative operators were used. Nuclear images have bad contrast; several solutions were then suggested to overcome this problem. Indeed, there are researchers who applied the Laplacian operator combined with other morphological operators to the factorial images or the images resulting from the Fourier analysis. Compared with original images, these images have better contrast. But unfortunately, factorial images often induce the two ventricles collision [13, 14]. Other researchers proposed to smooth images by a Gaussian filter before applying the canny detector to detect peaks which define a chart of reference points. This method is unfortunately applicable only on skeletal scintigraphic images, because skeleton can be characterized by reference points whose extraction is based on an anatomy a priori knowledge. Expert knowledge is represented by a set of parameterized rules which are used to boost the segmentation algorithm [22, 23]. In one of our work, an enhancement contrast step was proposed, before applying second derivatives operators. The retained enhancement method is linear and depends on two parameters. The value adjustment parameters is subjective and resulting images present imperfections due to detection of open and false edges [16, 17].

Active contours are also used. They are known by their ability to integrate the processes of detection and contours evolution in an only energy minimization process. But unfortunately, they suffer from their parameters estimation and initialization problems. The active contour, first introduced by Kass *et al*. [15], deforms an initial contour to seek the regions of interest. It is significant to note that this approach is particularly well adapted to object localization. This is why; these last years, active contours became very popular. In literature, two active contour frameworks are proposed: edge based active contour and region based active contour. The two approaches were used to outline left ventricle in scintigraphic images.

For those based on edges, contour evolution is exclusively controlled by gradient forces. Applied to scintigraphic data, the method suffers from the hard task of parameterization, as well as the great influence of initialization on contour convergence [19]. Contrary to edge based active contours, region based models exploit regions information. This approach was used in left ventricle delineation [12]. The proposed method uses the Mumford and Shah functional [20] and the `active contour of diffusion' proposed by Cremers [5]. Authors suggest introducing separating forces between the two ventricles in order to keep the two splines separated. But the method still depends to the initialization step and to method parameters. In addition, the used repulsion force depends only on the distance separating the control points from two ventricles. This can create a strong repulsion energy which can move away too much the two cardiac cavities.

When examining, the overview of the LV delineation, it is shown that the segmentation of scintigraphic images is a difficult task and it is sensitive to their characteristics. Results often depend on the method parameters whose adjustment requires a hard experimentation stage. The common solution consists in giving to operators the possibility of varying these parameters values. Another significant observation is the importance to incorporating a priori knowledge in the segmentation phase. In fact, pathological conditions, technical poor quality images and artefacts necessitate that segmentation algorithms use sufficient background knowledge of anatomy and spatial relations of ROI in order to work satisfactorily.

3. Motivation to Use the Statistical Deformable Models

When examining ventricle shape and texture in planar scintigraphic images, we noticed that these are two significant parameters which can be used for better locating it. To confirm this observation, we carried out simple tests on a set of real images. The set contains 25 images sequences whose acquisition is synchronized with the ECG. Each sequence is of 16 images; each one of 128x128 pixels and is coded on 8 bits. These sequences correspond to 25 diverse patients and present healthy and pathological coronary states:

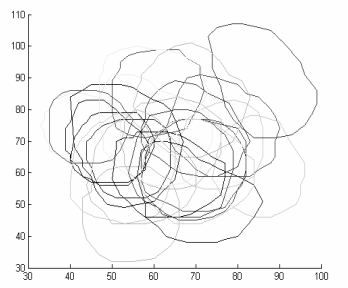
- The first test is used to study the shape variability of the LV, from an individual to another. To do this, we selected the same image of all the sequences. The LV boundaries are then marked. Figure 1 presents superposition of the 25 obtained boundaries.
- The second test is used to study the shape variability of the LV in the same cardiac cycle (the same individual). To do this, we selected two sequences from the database: a healthy case and a pathological one. We tracked then the LV in the same cardiac cycle. Figure 1(a) and (b) present the superposition of 16 obtained boundaries (for each case).
- The third test aims to study the left ventricle texture. In fact, three texture analysis parameters were used to study this variation: the mean, the variance and the entropy. Figure 2(a) shows some examples of the LV (corresponding to different moments of diverse cases). We note that the ROI were warped in order to eliminate the effect of shape variations. Figure 2(b) shows the texture parameters variation of the same set.

Figure 1(a) shows that the left ventricle shape varies from an individual to another, and this variation can be due to:

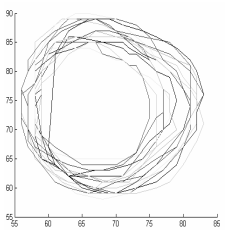
- The LV position and size, therefore to superpose a shape on another, it is enough to adjust the parameters relating to: rotation, scaling or translation.
- The main difference or shapes.

Figures 1(b) and (c) show that the LV shape varies little throughout the cardiac cycle. This variation is due mainly to the movement of this organ during the cycle. Indeed, the cardiac pump presents two states: the diastole (relaxation) and the systole (contraction) one. Figure 2 shows the weak variation of the texture parameters. In fact, the LV texture doesn't show an important variation in different sequences.

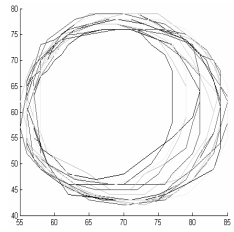
According to these tests, we conclude that the left ventricle shape and texture change little. This variation can be sometimes reduced to object position and size. These to parameters (shape and texture) are thus a significant a priori knowledge which can be used for its localization. This observation, motive us to explore deformable models that incorporate a priori knowledge about objects shape and texture. This class is known as: statistical models.



a. Superposition of 25 contours of the left ventricle obtained at the same moment of the cardiac cycle.

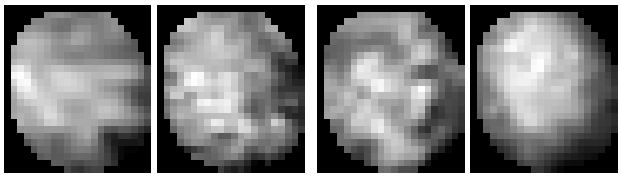


b. Superposition of 16 contours of the LV (healthy case).

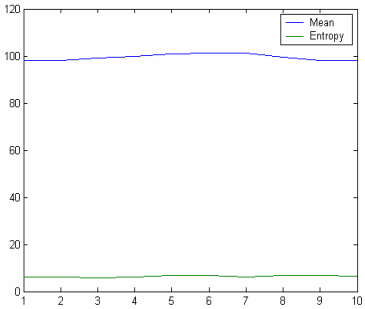


c. Superposition of 16 contours of the LV (pathologic case).

Figure 1. study of variation of the LV shape on a set of scintigraphic images.



a. Examples of left ventricles warped to the mean shape.



b. Extraction of some parameters for the texture analysis.

Figure 2. Study of the left ventricle texture variation on a set of scintigraphic images.

4. LV Localization Using Statistical Deformable Models

Initially, we will present the Active Shape Models (ASM). An improvement of this method will be proposed in order to exceed its limitations relating to initiation and training phases. Secondly, we will present the Active Appearance Model (AAM) which integrates in more the texture parameter.

4.1. Modelling the Left Ventricle Shape Using Active Shape Models.

ASM are originally proposed by Cootes *et al*. [2] for extracting complex and no rigid objects. The modelling technique is similar to snakes. The advantage of ASM is that the initial curve evolution is guided by a priori knowledge. This knowledge consists mainly on a statistical shape model, named Point Distribution Model (PDM), which describes the object mode variations. The construction of such model is done by applying the Principal Component Analysis (PCA) on a set of training images, presenting the possible shape variations of the object.

In the localization phase, will start with an initial estimation, placed near the target contour, and move progressively this estimation towards the studied object boundaries. The final shape, which must coincide with the object shape, should be in the "allowable shape domain" defined by the PDM.

4.1.1. ASM Building and Proposal Improvement

The two key steps in the AMS approach are consequently:

- Building the PDM.
- Using PDM to localize the object.

4.1.1.1. Building the Point Distribution Model

This step aims to model geometry and object variations. The PDM is a shape model which deduces from an aligned training set, the typical object variations. To obtain this model, we need to:

- Collect a set of training images containing the object in different positions.
- Extract the shape in each image by placing the landmarks.
- Align the shapes.
- Finally, determine the modes and amplitudes of variations by applying the PCA.

These steps are briefly described in the following sub-section. For more details, please refer to [10].

Step 1: training set selection and proposal improvement. This step consists to collect images set which covers the major variations of the studied object. It is a delicate step for the following reasons:

- The number of collected images should be relatively high in order to obtain a sufficiently representative model.
- The number of images should not be too high to reduce the complexity computation.
- The selected instances should be various in order to obtain an expressive model.

To reduce the complexity of this step, we propose a selection strategy to collect the training set. So, to optimize the number of images in this set; our idea consists to apply a clustering step which aims to group different sequences according to the ventricle shape. To do this, we propose to select the same image of each sequence. Our objective is to group the similar instances in the same class. Thus, shape deformations will be clustered in *K* categories. Each one represents a variability mode of the ventricle shape. To perform that, we must use an invariant space, where invariance by translation, rotation and scale is assured. Each shape will be then represented by an invariants set. To cluster theses shapes, we can simply cluster the invariants vectors corresponding to each shape.

In our application, ventricle shapes are represented by Fourier descriptors, known by their performance, and they are clustered using the *K*-Means considering its simplicity and performance. Shape deformations are thus separated to four classes. We can then choose arbitrarily some sequences from each class (for example 2 sequences). From each retained sequence, we select a number of images which represent the ventricle shape variation on a cardiac cycle. As example, in the first sequence, we choose the first image in diastole and the first image in systole. In the second sequence, we vary the images indices and so on until covering all retained sequences. Thus, we assure that each moment of the cardiac cycle is presented by an image. Finally we collect 16 images (in our case), which seem sufficient to introduce the majority of the ventricle position during the cardiac cycle.

Step 2: training set alignment. After having built the training set, shapes are marked by placing on each image a set of landmarks. It is a difficult task in the ASM approach, because it directly influences the PDM quality and consequently the object localisation. This task is generally entrusted to an expert (a doctor in our case). In general, the number of landmarks depends of the object complexity and the importance of the object details. In our case, 25 landmarks are sufficient to represent the left ventricle details. The shapes resulting of this step is not aligned as shown in Figure 3(b). Then, to study their variability, these shapes are aligned on one of them as shown in Figure 3(c). The mean shape is then deducing as Figure 3(c) and it is supposed to be representative of all shapes [10].

Step 3: statistics capture**.** After the alignment step, the training set containing *N* aligned vectors. These vectors can be organized in a matrix of size (*2n*, *N*) called observation matrix, whose columns correspond to the shape (vectors) and the lines correspond to the landmarks coordinates describing each shape. The problem now is how to deduce from this set the modes and amplitudes of deformation of the studied object.

That can be done by examining the variation of the homologous landmarks on all shapes. But the problem is that each shape is represented by *N* landmarks, each

one have an *(x, y)* coordinates. Therefore, for one landmark, there are *2n* variables to examine and for the totality of the landmarks there are *2Nn* variables. In order to simplify the problem and to reduce the number of variables which describe each shape, the PCA is applied. Consequently, each shape can be represented by a linear combination of the principal components. Then, any shape *X*, in the training set can be deduced using this equation:

$$X = \overline{X} + b_S P_S \qquad (1)$$

when: $\overline{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$ is a mean shape, P_s is a set of orthogonal modes of shape variation and b_s is a vector of weights which describes the projection of the shape X in P_S. When examining the equation 1, we can conclude that the point distribution model extracted from an aligned training set, define an authorized space of shapes named Allowable Shape Domain (ASD). This model will be used to impose deformation constraints during the localization phase. This can limit the space solutions and to obtain an acceptable shape. For more details, we recommend work of Hamarneh *et al.* [11].

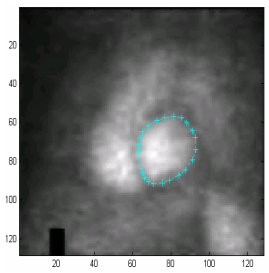
Step 4: gray levels modelling. In addition to the PDM model, Cootes [2] proposes to model the gray levels information from the training set. That makes possible to locate the optimal shape using image intensity information. The idea is to examine the gray level information around each landmark and to try to put it in a compact structure, which will be used to move the initial estimate towards the object borders in a new image. In general, any region around the landmarks can be considered and studied, but here we will concentrate on the gray levels only along a line passing through the landmark in question and perpendicular to the boundary formed by the landmark and its neighbours. This step details are exposed in the work of Hamarneh and *et al*. [11].

4.1.1.2. Using PDM to Object Localization

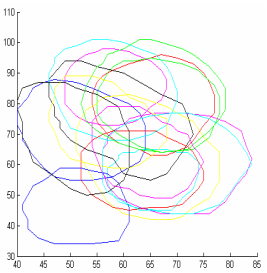
After building the PDM and modelling the gray levels information, the objective is to locate the ventricle shape in a new image. An initial estimation X_i is placed near the object and will be move gradually towards the studied object boundaries. This evolution is guided by the examination of the characteristics of the gray levels information around each landmark. It is then necessary to determine the shape and pose parameters to be applied on X_i in order to reach the new site X_{i+1}. This procedure is repeated until any modification is observed. The PDM will be used to force the procedure to converge only towards acceptable shapes. The localization procedure is thus done by sequentially repeating the following stages until convergence:

- Place an initial estimation on the image.
- Compute the necessary displacement to make.
- Compute the shape and pose parameters which perform this displacement.
- Update the pose and shape parameters to move X_i to X_{i+1}.
- Stop the procedure if convergence, else repeat the same process when starting from X_{i+1}.

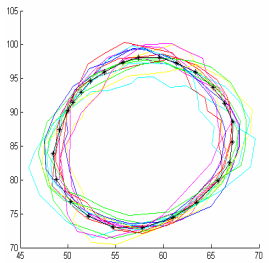
The localization can be optimized using the multiresolution research technique. Indeed, the procedure consists to start research in the highest level (weak resolution), then in the lower level and so on until the pyramid low level is reached (original image).



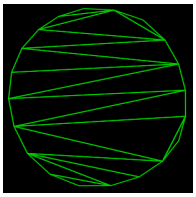
a. Shape extraction using 25 landmarks.



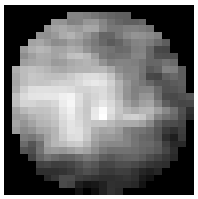
b. Not aligned shapes.



c. Aligned shapes.



d. Delaunay triangulation of the mean shape.



e. Shape free patch.

Figure 3. Training phase steps.

4.1.2. ASM Parameters Optimization and Minimization of Their Dependence to Initialization

Using the described method, first results show the ASM performance in left ventricle delineation. But we notice that these results depend of the method parameters. To optimize these parameters choice, we carry out many tests on real images. We note that the two parameters that interfere directly in the location step are:

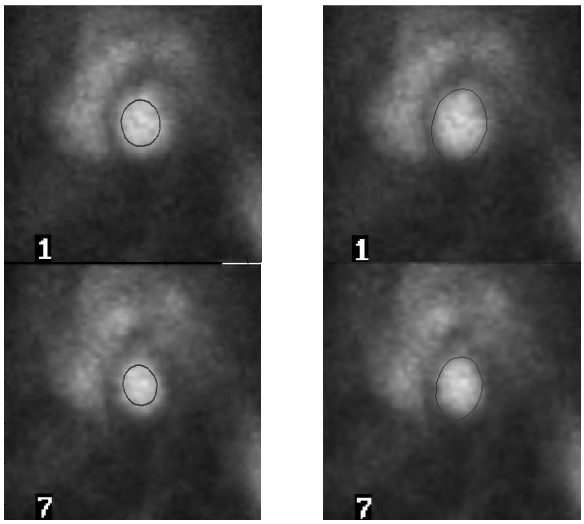
- The length of the search profile used in the gray levels modelling: while examining the obtained results, we notice that with reduced profile points under and above the characteristic point, localization is not satisfactory. While increasing the point's number, convergence improves. This is due to the fact that more the profile is long; more gray-levels model can better look for the closest profile. The profile length must also be reduced, to limit the computation complexity and to reduce the risk that the shape model overlap on the neighbor regions (especially in weak resolution). Tests show that a profile width of 21 points gives satisfactory left ventricle delineation.
- The number of pyramid level: using a reduced levels number, results are not satisfactory. The increase of pyramid level number results to a convergence improvement. This is due to the refined localization in each pyramid stage. However, for scintigraphic images, the number of pyramid level should not be too large. Indeed, these images are of low resolution in the pyramid top and so the localization may not converge because of the very bad objects resolution. This bad convergence (or even divergence, in some cases) will be reflected in all the other pyramid levels. Tests show that 3 pyramid levels are sufficient to explore scintigraphic images.

In the other hand, the initialization phase is a delicate task on which the ASM convergence depends strongly. Indeed, the expert or the user is invited to place the required ventricle contour. In our case, 25 landmarks will be placed. To reduce this task and to improve initialization, we propose the following steps:

- To use the mean shape deduced from the modeling phase.
- To superpose this shape on the center of the left ventricle.
- To consider this shape as an initial estimate.

4.1.3. ASM Results and Discussion

The model thus parameterized is used to delimit the left ventricle in several images. These images represent several moments of the cardiac cycle. They correspond to healthy and pathological cases. Figure 4 show the comparison between results obtained using the parametric active contours and those obtained using active shape model. It is clear that the parameterization of the classic active contour is a very difficult task. In addition, its convergence depends strongly on the initialization. The bad contrast of scintigraphic images can distort the localization in Figure 4(a). When using the shape model, the localization quality is enhanced as shown in Figure 4(b). These results were shown to specialists who expressed their satisfaction. However the method can be improved by modelling the texture variation in addition to the shape one. The principle of this deformable models class called Active Appearance Model (AAM) will be presented in the next section.



a. Results using parametric active contour.

b. Results using active shape model.

Figure 4. Comparison between parametric active contour and active shape model.

4.2. Modelling the LV Texture Using Active Appearance Models

To synthesise a complete image of an object or structure, both the shape and the texture of the object must be modelled. Then, statistical models can be built to represent shape variation, texture variation and the correlations between them. By "texture" we mean intensities or colours across the object.

There are correlations between the parameters of the shape model and those of the texture model across the training set. A combined appearance model is then built which controls both shape and texture [Cootes 1998].

4.2.1. AAM Building

The appearance model is determined in a similar way to that of the shape model. Prior to a PCA analysis, each image must be warped and normalized to obtain a generic 'shape free patch'. Thus, each image of the training set, is warped using a Delaunay algorithm triangulation as shown in Figure 3(d). This removes spurious texture variation due to shape differences. The normalization procedure is then necessary to limit the effect of the global lighting variation. Consequently, a shape free patch is created Figure 3(e). Additionally, the mean $\bar{g}$ of all training instances is determined and subtracted from each image. PCA then generates a multi dimensional gray space. Therefore, a gray level image can be reconstructed by:

$$g = \bar{g} + P_g b_g \quad (2)$$

where P_g are the eigenvectors describing the gray space and b_g are the reconstruction parameters. Shape and texture are often correlated, so the combined model is used to unify the shape and texture models. Having calculated both statistical models of the shape and texture (appearance), PCA can be performed on the concatenated vectors of the shape and gray level parameters b_g and b_s to remove correlation between them:

$$b = \begin{pmatrix} W_s b_s \\ b_g \end{pmatrix} = \begin{pmatrix} W_s P_s^T (x - \bar{x}) \\ P_g^T (g - \bar{g}) \end{pmatrix} \quad (3)$$

where W_s is a diagonal matrix of weights for each shape parameter, allowing the difference between the shape and the gray model and P_g are the eigenvectors describing the shape.

By performing PCA on *b*, a space of appearance and shape is created with a parameter *c* that affects both the shape and gray levels of the model:

$$b = P_c c \quad (4)$$

where P_c are the eigenvectors of the space and *c* the vector parameters space controlling both the shape and gray levels of the model. As in the shape PCA case, the combined model representation can be reduced by removing the smallest eigenmodes. It is safe to consider small-scale variation as noise.

After building the combined model, the second step is to approximate a new example by using AAM. During this stage, we try to find the parameters which minimise the difference between image and synthesised model instance. An initial estimation is placed in the image and the current residuals are measured. Generally, a good match is obtained in a few iterations [3].

4.2.2. AAM Parameters Optimization

To build the shape model, the texture model and the combined model, the number of used eigenvectors must be fixed. A series of tests were then carried out by varying the variance value.

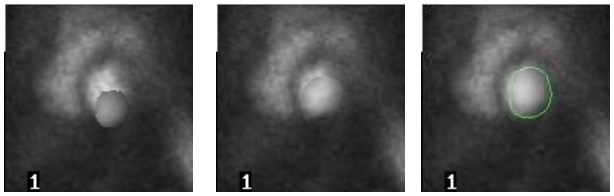
These tests show that the results obtained by using a variance equal to 60 (for the three models) approaches better the doctor annotation. Then this value is retained to better locate the ventricle and optimize the computation complexity [24].

4.2.3. AAM Results and Discussion

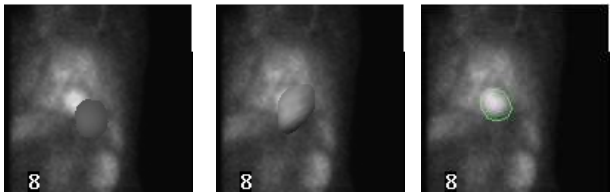
This optimal model was applied in several images selected at different moments of the cardiac cycle to assure the left ventricle appearance variation. AAM model converges after 12 iterations.

In comparison with the original image, the AAM seeks to minimize the difference between the synthetic image of the LV and the real image until the model equalizes this image.

Figure 5 shows some results in different iterations. According to these results, we notice that the AAM succeed to outline efficiently the left ventricle at any moment of the cardiac cycle despite the imperfections of nuclear images.



a. Diastolic image: 1iteration, 3 iterations, 7 iterations (3ms).



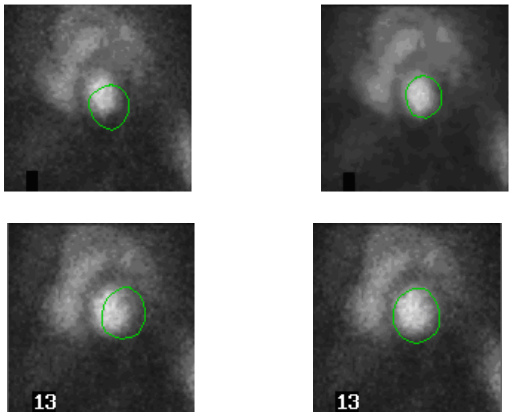
b. Systolic image: 1 iteration, 9 iterations, 12 iterations (4ms).

Figure 5 Evolution of the appearance model in the left ventricle search.

In order to show the importance of including texture information in the left ventricle delineation, we present in Figure 6, some results obtained by the shape model and by the combined one (using the shape and the texture models). We can then conclude that the left ventricle delineation using the combined model is better than the method using only the shape model. For computation complexity, Table 1 presents some results about the number of iterations required to the model convergence as well as the computation time (in ms). The tests were performed in a personnel computer $Intel_{(R)}$ $Core_{(TM)2}$ CPU, 1.60 GHz, 1.00 GO of RAM. The results were very encouraging. In fact, the execution speed can make possible the integration of this model in a real time machine which can be coupled to the gamma camera.

Table 1. Computation complexity of the AAM convergence.

Number of Iterations	4	8	9	5	11	9	5	8
Time in ms	7	5	7	6	7	5	9	7
Number of Iterations	4	6	7	3	8	7	4	6
Time in ms	5	4	6	5	5	5	7	6



a. Results using the shape model. b. Results using the combined model.

Figure 6. Comparison of the left ventricle delineation using the shape model and the combined model.

5. Evaluation of Left Ventricle Localization

To evaluate the left ventricle delineation using this deformable model, we considered 2 sequences corresponding to a healthy case and a pathological one. Two doctors were invited to outline the ventricle, twice, to reduce intra observer's variability. Next, we compute the left ventricle activity according to the automatic and the manual localisation. We then, compute a correlation coefficient between these two results. The Table 2 presents the obtained results.

We notice that the obtained correlation coefficients are good. Results show the good correlation between our results and those given by the doctors.

6. Using the Left Ventricle Localization for Some Diagnostic Parameters Extraction

We present here two parameters computed using the left ventricle delineation which are: the activity-time curve and left ventricular ejection fraction.

6.1. Activity Time Curve

The activity-time curve is a significant parameter in the study of the ventricular function. To plot this curve, it is necessary to locate the left ventricle in the 16 images of the sequence and to determine the corresponding activity at every moment. The activity corresponds to the number of scintillations contained in the left ventricle which are proportional to the pixels value in the ROI.

The activity-time curve was plotted for ten cases. Figure 7 presents two examples of these curves referring to the activity time curve of a healthy case, it is quite clear that the first case (in the left) correspond to a normal one. However, for the second case (in the right), the curve shape is far from the normal shape. Indeed, the curve presents a minimum in moment 6, and a maximum in moment 12. The curve corresponds then to a pathological case. This observation is confirmed by analyzing the ventricular ejection fractions of each case.

6.2. Ventricular Ejection Fraction

The Ventricular Ejection Fraction (VEF) is the proportion of blood ejected from the left ventricle with each heart beat. An EF of 50% indicates that the left ventricle ejects half its volume each time it contracts. A normal ejection fraction is of 50% or higher. A reduced ejection fraction indicates that the heart presents a difficulty to eject the blood [7, 6, 1].

By definition, the end-diastolic volume is the volume of blood within a ventricle before a contraction. Similarly, the end-systolic volume is the volume of blood left in a ventricle at the end of contraction. The difference between end-diastolic and end-systolic volumes is the stroke volume, the volume of blood ejected with each beat. The VEF is the fraction of the end-diastolic volume that is ejected with each beat; that is, it is stroke volume divided by End Diastolic Volume (EDV).

$$VEF=(EDV-ESV)/EDV \quad (6)$$

The VEF of the first case is 53 % and of the second case is 33%. The second value is very low what explains that the cardiac pump of the second subject has a difficulty to eject blood.

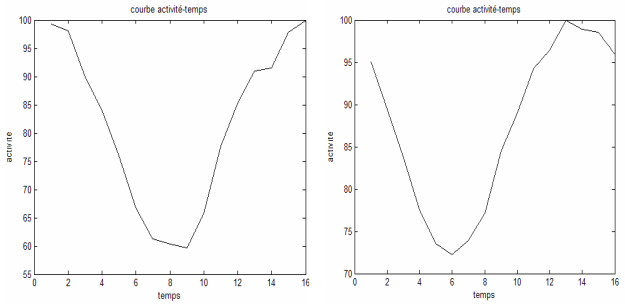


Figure 7. Examples of diagnostic parameters extraction (in the left: normal case, in the right: pathological case).

Table 2. Correlation coefficients between the ventricle activities obtained by the active model and those obtained by the manual annotation.

	Doctor 1		Doctor 2	
	Test 2	Test 1	Test 2	Test 1
Sequence 1	0.8436	0.8560	0.8910	0.9081
Sequence 2	0.8935	0.9110	0.9044	0.8911

7. Discussion and Conclusions

The deformable models showed their performance in several domains. In fact, they generally produce good results. The generality of their principle gave birth to several approaches according to the problems characteristics and the proceeded images. This makes

difficult the definition of an applicable general model for all the applications. In nuclear imagery, the left ventricle tracking is a delicate task seen the specificity of the scintigraphic images. In fact, these images have a weak contrast and a bad resolution, what presents an obstacle for their segmentation. To these difficulties, is added the problem of the fluctuation statistics witch makes more difficult the ventricle delineation. The choice of the statistical deformable models is motivated by their performance, and the specificity of the ventricle shape and texture that can be included in the research phase. Our contribution lies in the improvement of the training set selection and the initialization step. This improved method was applied on several images sequences and the found results are satisfactory. These results were used to extract diagnostic parameters.

Finally, we signal that, actually, we address the problem of the left ventricle movement follow-up in scintigraphic image sequences using a method which is based on a spatio-temporal a priori knowledge. This method contains two phases: a training phase which aims a spatio-temporal modeling for variation of the studied object; and a localization phase, which uses the training phase results to locate the studied object in a new sequence. Preliminary results show the success of this approach to the left ventricle tracking in image sequences [8].

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