Using the Active Appearance Models for the localisation of the left ventricle in planar scintigraphic Images

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Abstract - *Statistical deformable models are powerful priori knowledge based technique for the delineation of the non rigid objects in images. The widely-known algorithms allowing such a priori information incorporation is the Active Shape Models (ASM) and the Active Appearance Models (AAM). In this paper, we focus on the detection of the left ventricle boundaries in planar nuclear imaging using AAM. In fact, this model cannot only incorporate the shape information but also the texture of the region of interest. Several tests were applied on a set of real images to optimize the choice of some model parameters. Results show the performance of the AAM method thus parameterized.*

Keywords: Cardiac nuclear images, left ventricle, deformable models, Active Appearance Models.

1 Introduction

Nuclear medicine is a healthcare speciality involving the use of radioactive compounds to perform diagnostic imaging examinations that can lead to the effective treatment of many diseases. Although nuclear medicine is often considered as an independent discipline, it is closely related to radiology since radiation is used to develop images of human anatomy. Cardiac nuclear medicine refers to these diagnosis tests that are used to examine the heart function and anatomy.

Several localization methods were applied to delimitate the left ventricle because of the importance of this muscle in pumping blood through the body. But, none of these techniques was sufficient to successfully detect the left ventricle boundary particularly with cardiac nuclear images.

Other segmentation techniques using a priori knowledge about the ventricle are always proposed. This approach can boost the performance of the left ventricle delimitation. A widely-known algorithm allowing such a priori information incorporation is the statistical deformable models such as the Active Shape Models (ASM) method. This shape model was used by Khalifa and al. [1] to delimitate the left ventricle.

However, in order to maximize the priori knowledge of the cardiac nuclear images, it is better to use grey-levels information, through objects of interest, further than only shape informations. Active Appearance Models (AAM) holds this information in consideration.

In this paper, we try to delimitate the left ventricle boundaries using the AAM. In the second section, we present the advantage of using this method based on deformable models. In the third section, we describe the AAM method witch is interested in informations about both the shape and texture inside the objects. Then, we present its building steps and some examination tests.

2 AAM for left ventricle localisation

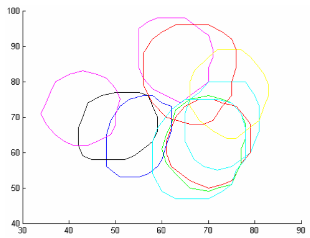
The ASM is a segmentation technique, introduced initially by Cootes and al. [4] with the intention to extract complex and not rigid objects. The advantage of this approach is its ability to incorporate a priori knowledge about the shape object and its deformation modes, to guide the progression of an initial curve to the real object boundaries.

The major advantages of AAM are their ability to integrate a priori knowledge about the explored object. In fact, they can represent the variations in shape and/or texture (intensity) of the target objects.

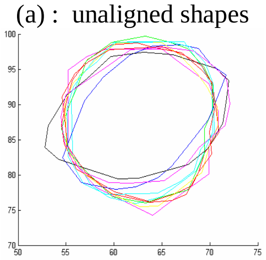
If the ASM seeks to match a set of model points to an image, constrained by a statistical model of shape, the AAM seeks to match both the shape and the object texture in the image. So, the AAM extends the ASM to include texture information instead of just the edge profile along landmarks. In fact, this method is used to extract useful features not only about the shape but also the grey-level information inside the objects.

When examining the shape and the texture of the left ventricle in nuclear images, we notice that these two parameters change little and then, they can be used to better delimit its boundaries. In order to confirm this observation, we have carried out some tests in order to study the texture and the shape variation in a set of real cardiac nuclear images.

The first test consists in the follow up of the left ventricle in 10 different cases. This test was applied referring to an expert. The obtained shapes are aligned in order to retain only the main difference in shape. The steps of this test are shown in figure1. It is important to note, that the ventricle was traced in the same instant of the cardiac cycle (for all the cases) and that the shapes are aligned to obtain a true shape representation without translation, rotation and scale effects.



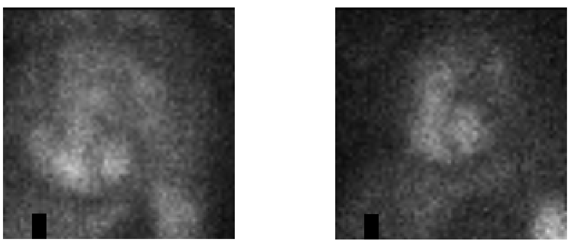
(a) : unaligned shapes



(b) : aligned shapes

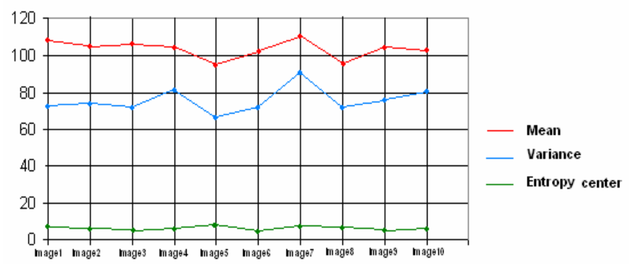
Fig. 1: Left ventricle shapes

The second test aims to study the texture variation of the left ventricle. For the same ventricles, three textural analysis parameters were then computed witch are: the mean, the variance and the entropy center. Figure-2.a shows some examples of the extracted left ventricle. We note that, the ventricles were warped in order to have the same shape which is the mean one (Figure-2.b). This step is done in order to eliminate the effect of shape variations. The texture parameters were shown in figure-2.c.



(a) Examples of cardiac nuclear images

(b) Corresponding extracted shape-free images



(c) Parameters variation

Fig. 2: Study of the texture variation through the left ventricles of cardiac nuclear images.

The performed tests show the weak difference in shape and texture of the ventricles, although they correspond to healthy and pathological cases.

We can conclude then, that the left ventricle shape and texture don't show an important variation. The integration of a priori knowledge about shape and texture of this organ could be helpful in its delimitation.

In the next section, we briefly present the AAM principle, which aims to modelize the shape and the texture of the non rigid objects, in order to boost their localisation performance.

3 Active Appearance Model building

Initially, the ASM were created. In addition to the shape variation, the AAM incorporates the object texture variation in order to help more the localisation step. In fact, an Active Appearance Model contains a statistical model of the shape and the grey level appearance of an object of interest, which can be fitted rapidly to an example in a new image. During a training phase a model instance is randomly displaced from the optimum position in a set of training images. The difference between the displaced model instance and the image is recorded, and linear regression is used to estimate the relationship between this residual and the parameter displacement.

To build the Active Appearance Model, two models are then built namely the shape and the appearance models.

To build the shape model, we have followed these steps:

--Collecting a training set, showing the maximum of possible variation of the object shape.

--Extracting the object shape from images by putting landmarks (this step is generally confided to an expert).

--Modelling the shape variation.

The modelling shape step result is the creation of a shape model, which can be represented by the following relation:

$$X = \overline{X} + b_S P_S \tag{1}$$

Where X is the synthetic shape, $\overline{X}$ is the mean shape, P_s is a set of orthogonal modes of shape variation and b_s is a set of shape parameters.

To build the appearance model, we proceed in a similar fashion to that of the shape model. Prior to a "Principal Component Analysis"(PCA), each image must be normalized and warped to obtain a generic 'shape free patch'.

Therefore, a grey-level image can be reconstructed by:

$$g = \overline{g} + P_g b_g \tag{2}$$

Where $\overline{g}$ is the mean normalised grey-level vector, P_g is a set of orthogonal modes of variation and b_g is a set of grey-level parameters.

Having calculated both statistical models of the shape and texture (appearance), PCA can be performed again, this time on the concatenated vectors of the shape and grey-level parameters b_g and b_s to build the combined appearance model:

$$b = \begin{pmatrix} W_S . b_S \\ b_g \end{pmatrix} = \begin{pmatrix} W_S . P_S^T (x - \overline{x}) \\ P_g^T (g - \overline{g}) \end{pmatrix} \tag{3}$$

Where W_S is a diagonal matrix of weights for each shape parameter allowing the difference between the shape and grey 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 the gray levels of the model:

$$b = P_C c \tag{4}$$

Where P_c are the eigenvectors and c is a vector of appearance parameters controlling both the shape and grey-levels of the model.

Consequently, a shape and an image can be generated by the model from the following equations:

$$x = \overline{x} + P_S W_S^{-1} P_{c,s} c \tag{5}$$

$$g = \overline{g} + P_g P_{c,g} c \tag{6}$$

$$P_c = \begin{pmatrix} P_{c,s} \\ P_{c,g} \end{pmatrix} \tag{7}$$

The image g is then re-warped from the mean to the new label locations given in x.

It is important to notice that an eigenvector is a set of displacement vectors, along which the mean shape is deformed. So, the combined model representation can be reduced further by removing the smallest eigenmodes. It is safe to consider small-scale variation as noise. Thus to retain p percent of the combined variation in the training set, t modes can be chosen satisfying the following condition:

$$\sum_{i=1}^{t} \lambda_i \geq \frac{p}{100} \sum_{i=1}^{2n} \lambda_i \tag{8}$$

In the following step, and during image search, we wish to find the parameters which minimise the difference between image and synthesised model instance. An initial estimate of the instance is placed in the image and the current residuals are measured. The relationship is then used to predict the changes to the current parameters which would lead to a better fit. A good overall match is obtained in a few iterations. For more details, please refer to [2], [3] and [5].

4 Optimization of model's parameters

To build shape, texture and combined models, we have to optimise some parameters such as the number of eigenvectors and the number of images in the training base. These two parameters have a great influence on the localisation result.

A variety of tests were performed by varying the number of eigenvectors in order to have better results.

Noting that this number influences directly the variability in shape and texture presented by the generated model.

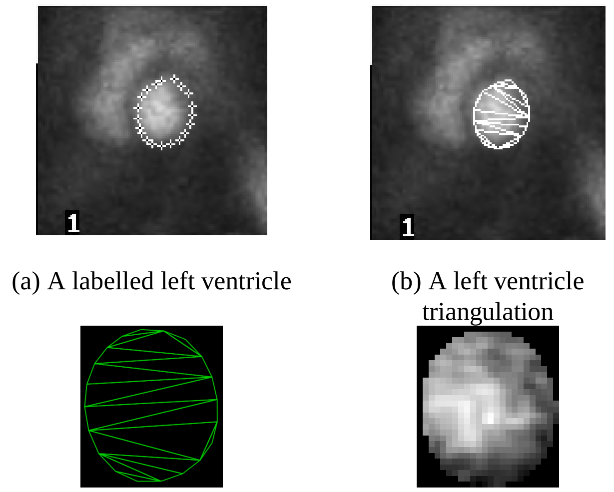
In our case, 60% of the model variations are enough to give better results and to reduce the computation complexity.

Another set of tests were conducted in which we have varied the number of images in the training set. Those tests show that the increase of the number of images guaranteed different variations of shape and texture. But, it is important to note that the increase of images number need more computation. So, a number of 60 images hold in different instants of the heart cycle seems to be an optimal choice.

5 Results and discussion

In the training phase, we have to collect a set of images. We selected images coming from 10 sequences of heart scintigraphic images, corresponding to 10 different patients. Every sequence holds 16 images having 128x128 pixels. From each sequence, six images are then chosen to compose a training set of 60 images. These images represent different instance of the cardiac cycle (systole, diastole…).

These images are first labelled (figure-3.a) and aligned (figure-1.b).



(a) A labelled left ventricle

(b) A left ventricle triangulation

(c) Delaunay triangulation of the mean shape

(d) Shape free image

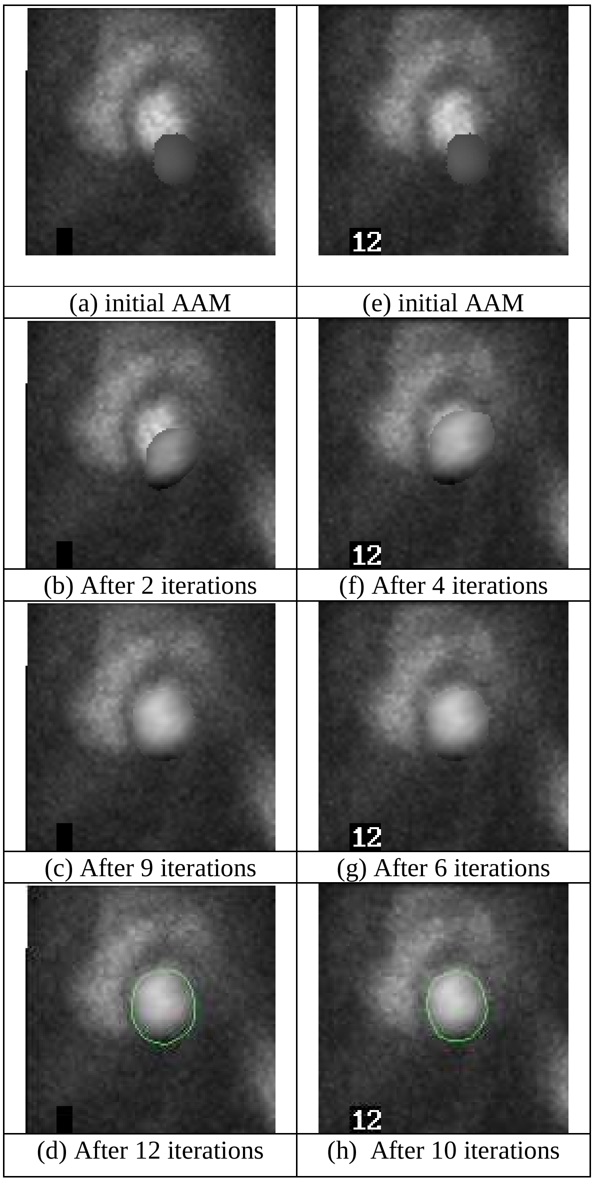
Fig. 3: The steps of building the appearance model

Additionally when building the appearance model, to accommodate for global lighting variation, each image is normalized and warped (using a Delaunay triangulation) to the mean shape to obtain a "shape free patch."

Figure-3.c shows an example of a triangulated left ventricle and figure-3.d shows the result of warping stage of the ventricle in order to have a "shape free image".

Finally, the combined shape and appearance model is built. It modelizes the relationship between both shape and texture. Given proper training, the built models can then be used in iterative searches to locate specific areas of interest in the scintigraphic images.

In the localization phase, the final model is put near the left ventricle. Then, it progresses to fit perfectly the object of interest. Some examples of the localisation step evolution are given in figure-4. In these examples, the model fits the left ventricle after 12 iterations for the first image and after 10 iterations for the second one.



(a) initial AAM

(e) initial AAM

(b) After 2 iterations

(f) After 4 iterations

(c) After 9 iterations

(g) After 6 iterations

(d) After 12 iterations

(h) After 10 iterations

Fig. 4: Left ventricle search examples

From these results, it can be seen that the final texture matches the ventricle boundary quite well. To validate the method, a variety of tests were performed using several images taken from both healthy and pathological heart. The obtained results were considered satisfactory by nuclear physician. Compared with the classic deformable method used to localize the left ventricle witch is the ASM, this method proves its robustness even when the contour is not well defined.

6 Conclusion

Nuclear imaging is a powerful tool to study the coronary state. Unfortunately, these images have a bad contrast and a weak resolution. To localize the boundaries of the left ventricle in this image modality, the classic segmentation methods do not give satisfactory results. Using deformable models seems to be a good idea since they are a priori knowledge based approach. Specially, Active Appearance Models showed their ability to localize non rigid objects despite the noisy images. The combined appearance model lends many interesting opportunities since it modelizes the relationship between both shape and grey texture. So, the obtained results, using optimal training set and the appropriate parameters were considered satisfactory.

7 References

[1] N. Khalifa, S. Bettaîeb, K. Hamrouni , N. Ellouze. “Localisation du ventricule gauche dans des images scintigraphiques planaires par modèles à formes actives déformables”. TAIMA 2007, pp 147-154, Tunisie 2007.

[2] T.F. Cootes, G. J. Edwards and C. J. Taylor. “Active Appearance Models” IEEE Transactions on Pattern Analysis and Macine Intelligence, Vol. 23, NO. 6, June 2001.

[3] T.F. Cootes and C.J.Taylor. “Statistical Models of Appearance for Computer Vision1”. Imaging Science and Biomedical Engineering, University of Manchester.U.K. 2004.

[4] T.F. Cootes, C.Taylor, D.Cooper and J.Graham. “Active Shape Models"-Their Training and Application”. Computer Vision and Image Understanding, January Vol. 61, No. 1, pp 38-59. 1995.

[5] T.F. Cootes, G.J. Edwards et C.J. Taylor. "Active Appearance Models".In Proc. European Conference on Computer Vision 1998 Vol. 2, pp. 484-498. Springer. 1998.