LV segmentation using Active Shape Model(ASM)-A Case study

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1 Introduction

In this report, we will present our work regarding the segmentation task for Left ventricle(LV) endocardium of the cardiac on each diastolic and systolic images. Cardiovascular disease consider one of the heights disease that people might counter. The cardiac contractile function can be quantified through ventricle volumes, masses and ejection fraction, by segmenting the left (LV) and right (RV) ventricles from cine MR images .
Observing the the LV using MRI which consider a reference examination arise an important of this task for many reason, first, variability of the image among the patient so that make the manual segmentation non a trivial task and tedious. Second, help for speed up the diagnosis of disease and save the time of the practitioner. One of the well-known methods used to achieve the task is Active Shape Model proposed by Cootes [1] which we will present in this report specifically guided by the PhD thesis published by Carlos Santiago [3].

2 Active Shape Model

Active Shape Model consider a wide method used to segment objects with large variability by building a statistical model for the object using the data available for shape in different variation then using this model to fit the desired object.
ASM depends on prior knowledge information, shapes, and sometimes gray level information of the training images which doesn't require an intensive training operations. see Appendix

3 Data Set

The training data set used are the ACDC data which contains images for 100 patients stored in the nifti image format.
Each patient directory consist of five nifti files. Two 3D files(volumes) related to the labeled ground truth (GT) slices of the end-systolic and end-diastolic and

another two files related to the original slices. The last file is the 4D nifti file which has an added frame parameter for the motion of the cardiac slices.Each volume consist of different number of slices ranges from 6-18 and also some image slices has different pixel resolution.

4 Implementation

4.1 Model

As mentioned in the theory part, see **6.1** in Appendix , To build the model we need training data. and for a statistical shape model our approach requires the training data to be represented as shapes. This can be acquired from ground truth images because it has a manual segmentation for the LV endocardium and is done by an expert.

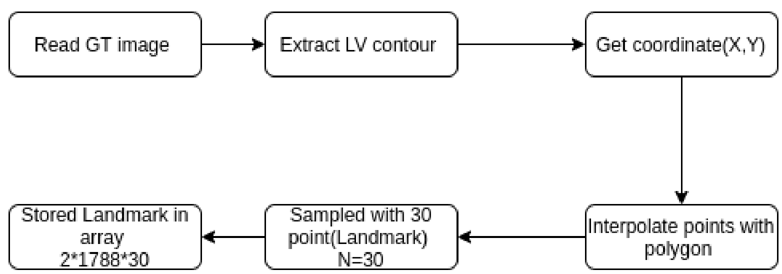

Figure 1: FlowChart

4.1.1 Read Ground Truth image

First we need to access the ground truth images from the nifti format file to be able to manipulate the GT image to apply some preprocessing operations on the image. Access the nifti file data can be done using **SimpleITK** and **Nibabel** python packages. So for the GT files, a numpy array of 3D shape (width, height, Slice) will be returned, where **Slice** is the number of the required GT slice.

4.1.2 Extract Contour

Each ground truth image is labeled with four intensity values [0,1,2,3] where each value classify the manually segmented objects RV, LV myocardium and LV endocardium respectively and the zero value is for the background. Since the task is to segment the LV endocardium so what is important is the boarder of the yellow region (LV) in the image below which is labeled by intensity color 3. So to only have the LV endocardium contour we extracted a new image with two label values 0 and 3. see the second image in Fig 2.By applying canny filter on the new image we get the boarder of the LV cavity. see the third image in Fig 2. This process is done on all the GT slices for all 100 patients which give us 1788 images of LV endocardium contours.

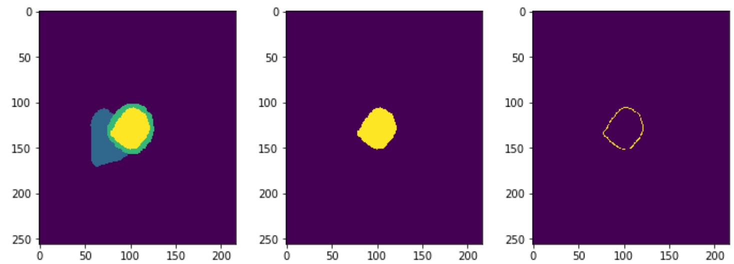

Figure 2: Ground Truth and the extraction of the LV Endocardium contour

After having the contour of the LV we will be able to extract the coordinates of the contour related to the LV. Because building the model requires having a training data of shapes, each shape consist of (x,y) coordinate points. see Fig 3

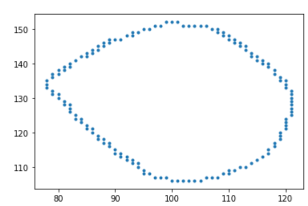

Figure 3: Plot the coordinates of the LV contour

4.1.3 Interpolation And Sampling

- **Problem:**
  Statistial shape model requires a training data of shapes with the same number of landmark points where each landmark point is a feature point that capture the variation of the shape. After that we will be able to form a $2N \times M$ Matrix where N is number of landmarks and M is the number of shapes (frame) for all volume that we have in end-systolic and end-diastolic phase. see **6.1** in Appendix
  In our case the result is different where each shape has different number of points hence a different number of dimensions. So it is not possible to form a $2N \times M$ the matrix see Fig 3. So we need to find a good approach where we can sample each shape to specific specific number of landmark points.

- **Solution:**
  One of the solutions is to sample the contour starting from one initial point

and take a fixed step around it but it is not easy to implement because all the points are distorted. So in our case to be able to solve the problem the solution was to form a polygon from shape points and then find its convex which represent the shape by the smallest number of points. The result is a new shape polygon with good approximation to the original shape with a specific number of points. see Fig. 4. The original points are represented in blue and the sampled points are in red which are the convex points of the polygon that contains the original points. And as you can see the sampled points can preserve the shape.

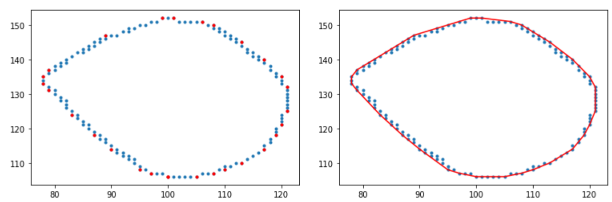

Figure 4: Point and Line representation after convex hull

After having each shape represented by its polygon sampled convex it becomes possible to alter each shape's number of points by choosing an initial point and move a fixed step around the perimeter of the polygon. see the right image in Fig4 where the sampled points are connected through red line segments and form a polygon. After applying the solution all the shapes has been represented with 30 landmark points So now we are able to build a $2N \times M$ matrix which is in our case $2 \times 30 \times 1788$ see Fig 5.

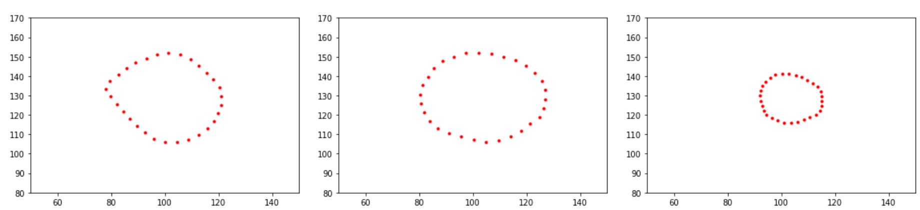

Figure 5: Different variation of a Volume with 30 sampled landmarks

4.1.4 Shapes Alignment

The model also needs the shapes to be aligned, translated, rotated and scaled to the same reference shape(frame), so in our case Procrustes analysis has been used to align all the shapes where the first shape in the data set is considered as the reference shape. see **Algorithm 1** section **6.1** in Appendix

In **Fig** 6, you can see in the first image the shapes before applying the Procrustes analysis where most of the shapes have different positions, rotations

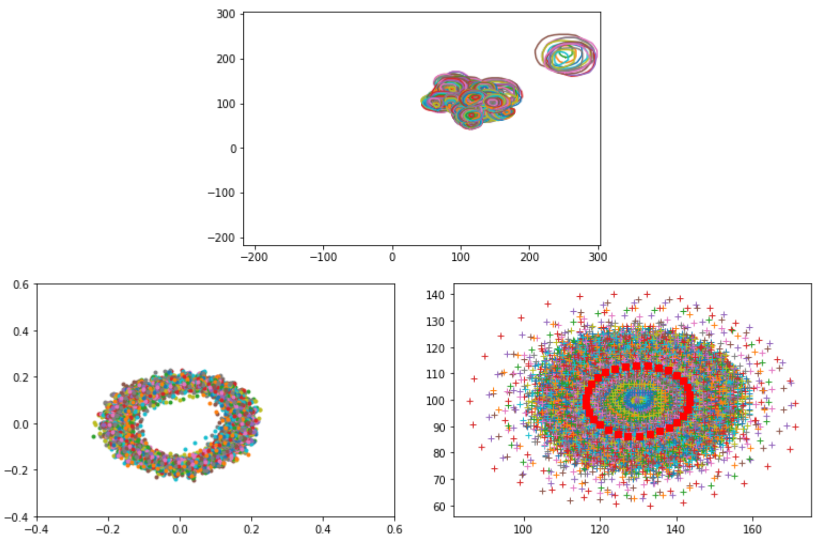

Figure 6: Aligned Shapes

and scale values. The left image below have all the shapes translated, rotated, and scaled but in comparison with right image below the scale parameters are not set where you can see all the shapes are centered around the mean shape(red shape) but with different scale.

4.1.5 PCA

The following step is applying PCA on the aligned dataSet, the theory and equation behind this is explained in Appendix section **6.3**.
For more convenient an already implemented function built in **Sklearn** package was used however implementing the idea it's pretty straightforward. In order to suite the data for applying PCA Function the input should be a 2D array, Therefore, we need to reshape the data set. The extracted data set is a 3D matrix with $2 \times 30 \times 1788$ shape, where 1788 are all the shapes in the data set with 30 landmarks representing each shape and 2 for the x and y axis. this matrix has been reshaped to 1788×60 where we flatten 30×2 landmarks for each shape as a one vector 60×1 to have a 2D matrix with shape 1788×60. After applying PCA, it was possible to obtain the mean shape, Eigenvectors, Eigenvalues of the Covarience matrix of the data. the result is point distribution model(PDM). the number of mode that describe the 0.99 of the data is 38 mode.

4.2 Fitting Model to Image

This step is the main one to interpret the test image that we need to perform the segmentation on it. In the following we will explain the problem and our

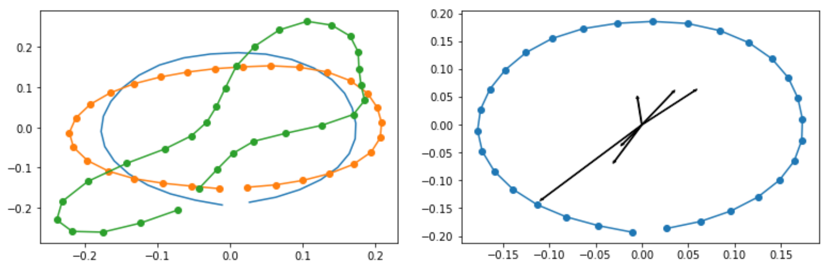

Figure 7: Left:two different variation for eigenvalue b , Right:eigenvalue with mean shape

attempt to solve it.
Iterative algorithm (2) explained in section **5.4** in Appendix applied to match the model point to target. it is worth mentioning that applying equation to perform it was a main challenge.
First,in order to prepare the image target to find the initial point,we applied image processing on it like median filter to smooth the image and canny edge detector to extract the edge in order to perform the searching along the norm towered it. Also many edge detectors have been tested like Sobel ,Robert...etc. In addition,initial start shape is required to perform ASM. Therefore, there are two ways to initialize this either by user interaction to specify the desired region (semiautomatic) or find this point automatically by finding the Region of Interest. our program perform two approachs.

As the result, there is a lot of secondary edges around the interesting area so when we put initial shape and start to search for edge along the normal , the result will be far from the required edge ,hence the shape will not be able to deform in proper way to fit the LV completlety. Coots [1] mention this problem and the solution for this is to build grey level profile model along the normal.so instead search to edge we can compere the the grey level value in the examined image with the profile.

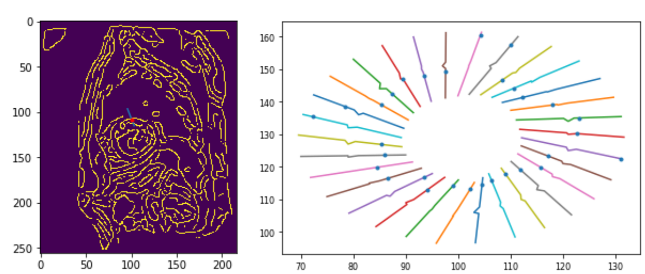

Figure 8: edge image with normal to point Model

4.3 Results

The final segmentation results did not deform well or as expected.see Fig 8 image 2 and as been explained in section **4.2**, noisy landmark points is detected. The results can improve by choosing the right filter either Sobel or Canny or any other image processing operations that can facilitate the finding of the corresponding edge point.

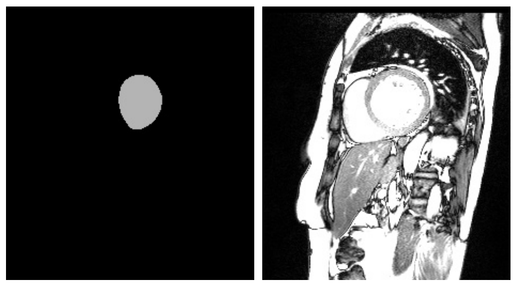

Figure 9: Segmentation results, Canny filter

5 Conclusion

LV endicardium automatic segmentation using active shape model has been implemented.One of the challenges we faced to implement ASM is that a lot of time and work was dedicated to discover the way to build a point distribution model which **ASM** requires given that **ACDC** data set doesn't include landmarked to use i direxctly as all papers that we reviewed assumes that landmarks is already given. The segmentation result we have obtained from applying the standard ASM were not optimal and it doesn't deform well as expected. To enhance the result a gray level mode should be developed beside the statistical Shape. this modification was built by Tom De Keyser Tina Tina Smets [4], we examined this implementation but we did not get a good result due to difficulty to build appropriate grey level model that suits our data.

6 Appendix

6.1 Shape representation

Asm based on building statistical Model from set of points(Landmarks). these landmarks should describe the variation of the object and also could be any features that distinct the region. Let choose N landmarks as training set to describe each shape. see vector 1

$$\tilde{x} = \begin{bmatrix} \tilde{x}^1 \\ \vdots \\ \widetilde{x}^N \end{bmatrix} \tag{1}$$

where $\widetilde{x} \in R^{2N\times 1}$, vector and $\widetilde{x}^i \in R^2$ is x^i, y^i coordinate for i-th point. Next, Let M is the number of training set for different shapes. We include them in one big matrix 2NxM.
the goal is instead of describing the shape by its points, we can represent it by mean shape, Eigenvectors and crosponding Eigenvalue (equation2)

$$x = \bar{x} + Pb \tag{2}$$

here each column of P corresponds to a specific deformation mode, and $b \in R^{L\times 1}$ are the deformation coefficients that determine the contribution of each deformation mode. and similarly to each point of model we can describe it in the same way. see equation(3)

$$x^i = \overline{x}^i + D^i b \tag{3}$$

benefit from the fact that the Eiginvectors preserve their direction even if we applied transformation on shape point and we can control the magnitude of it by changing the the eigenvalue.

6.2 Build a statistical model of the shape

After forming the shape Matrix two important steps should be taken.
First, **Align** all shape in training set to one axis shape. It could be the mean shape or first one. This is to be able to compare equivalent point from different shapes. we achieve this by applying scale,rotation and translation for each point to the reference shape. Then make sure to minimize the square of distance between the points (4) .A Well-known process is used, called Procrustes analysis.

$$\widehat{a}, \widehat{t} = \arg\min_{a,t} \left(\widetilde{x} - \widetilde{x}_{\text{ref}}\right)^\top \left(\widetilde{x} - \widetilde{x}_{\text{ref}}\right) \tag{4}$$

Algorithm 1:

Result: Aligning a Set of Shapes

1. Translate each example so that its centre of gravity is at the origin.
2. Choose one example as an initial estimate of the mean shape and scale so that $|\overline{\mathbf{x}}| = \sqrt{\bar{x}_1^2 + \bar{y}_1^2 + \bar{x}_2^2 \ldots} = 1$
3. Record the first estimate as $\overline{\mathbf{x}}_0$ to define the default orientation.
4. Align all the shapes with the current estimate of the mean shape.
5. Re-estimate the mean from aligned shapes. [1]

6.3 Compute Model Deformation

by applying principle component analysis(PCA) on the the aligned training set. PCA helps to reduce the dimensionality by form a covariance matrix (6) of data and mean shape (5),then finding Eigenvector and Eigenvalue (7) of the the covariance matrix S in (6). "Instead of analyzing each point independently.Hence,they consider each shape as a single point in a 2N dimensional space (the vector $\widetilde{x}$). They determine the so-called allowable shape domain" as the region inside which training shape points exist. Within this region, it is possible to create new shapes that will be similar to the ones in the training set.

$$\overline{x} = \frac{1}{M} \sum_{j=1}^{M} \widetilde{x}_j \tag{5}$$

$$\mathbf{S} = \frac{1}{M} \sum_{j=1}^{M} (\widetilde{x}_j - \overline{x}) (\widetilde{x}_j - \overline{x})^T \tag{6}$$

$$\mathbf{S} P_l = \lambda_l P_l, \quad l = 1, \ldots, 2N \tag{7}$$

where P$_l and$ λ_l correspond to the l^{th} eigenvector and eigenvalue, respectively. Each eigenvector $P_l \in R^{2N}$ can be viewed as a displacement vector related to a specific mode of deformation, and l is the corresponding variance on the training set. The eigenvectors associated to the largest eigenvalues correspond to the most significant modes of variation. Since most of the variation can be explained by just a subset of the eigenvectors, the ones associated to smaller eigenvalues can be discarded to reduce the dimensionality of the representation. This is typically done by using only the first L eigenvectors such that these account for a large proportion of the total variation.[3]

$$L : \sum_{l=1}^{L} \lambda_l > r \sum_{k=1}^{2N} \lambda_k \tag{8}$$

Typical values for the proportion parameter are r $\in [0.9, 0.98]$".[3]

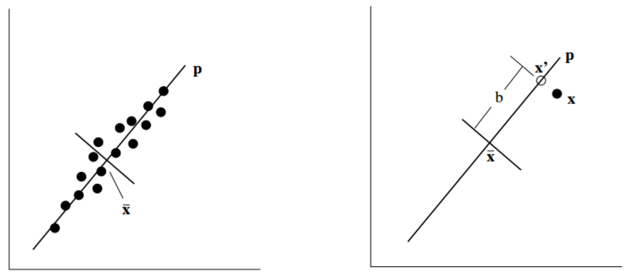

Figure 10: Applying a PCA to a set of 2 D vectors. **p** is the principal axis. Any point **x** can be approximated by the nearest point on the line, $\mathbf{x}'$ [2]

6.4 Fitting Model to new image:

Now, we have the flexible model point(PDM) which is described by the eigenvalue b and the corresponding eigenvector P. the next step is fitting this model in new image to segment the object of interest. since the model is scaled and aligned to mean shape when we train the model, finding pose parameter (rotation, translation , scale) to move the initial model x is important to transfer it form model coordinate to the image coordinate and this can be done by Euclidean transformation. After that we start to search along the norm of each model point to find the edges of the object in the image (Y). this will be the image point that we can use to adjust the shape b and the pose parameters to a better location. moreover, it is important to enforce constrain in b to be sure that shape will remains similar to those exist in training set.

Iterative method was proposed by coots to do this which is summarize in next Algorithms and more explanation in section **2.3**.

Algorithm 2:

Result: Match point to target Points

1. Initialise the shape parameters, b, to zero (the mean shape).
2. Generate the model point positions using $\mathbf{x} = \overline{\mathbf{x}} + \mathbf{Pb}$
3. Find the pose parameters (X_t, Y_t, s, θ) which best align the model points x to the current found points $\mathbf{Y}$.
4. Project $\mathbf{Y}$ into the model co-ordinate frame by inverting the transforma$tion T$:

$$\mathbf{y} = T^{-1}_{X_t, Y_t, s, \theta}(\mathbf{Y})$$

5. Project y into the tangent plane to $\overline{\mathbf{x}}$ by scaling: $\mathbf{y}' = \mathbf{y}/(\mathbf{y}.\overline{\mathbf{x}})$.
6. Update the model parameters to match to y $'$

$$\mathbf{b} = \mathbf{P}^T(\mathbf{y}' - \overline{\mathbf{x}})$$

7. If not converged, return to step 2. [1]

Algorithm 3:

Result: Active Shape Model

1. Examine a region of the image around each point $\mathbf{X}_i$ to find the best nearby match for the point $\mathbf{Y}$.
2. Update the parameters $(X_t, Y_t, s, \theta, \mathbf{b})$ to best fit the new found points $\mathbf{X}$.
3. Apply constraints to the parameters, b, to ensure plausible shapes (eg limit so $|b_i| < 3\sqrt{\lambda_i}$).
4. Repeat until convergence.[1]

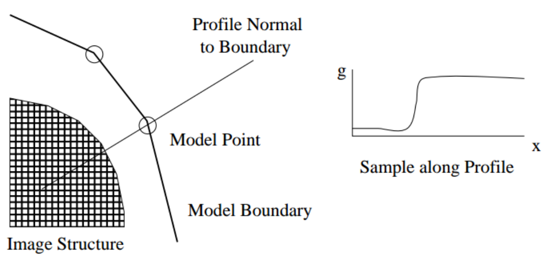

Figure 11: Sampling along Normal of Mdodel Point [2]

It should be noted that this fit measure relies upon the target points, $\mathbf{Y}$ begin the correct points. If some are incorrect, due to clutter or failure of the edge/feature detectors, Equation (9) will not be a true measure of the quality of fit.

References

[1] Timothy F Cootes, Christopher J Taylor, David H Cooper, and Jim Graham. Active shape models-their training and application. *Computer vision and image understanding*, 61(1):38–59, 1995.

[2] Ed.R.Baldock and J.Graham. *Image Processing and Analysis*. Number 1. 07 2000.

[3] Carlos Santiago. *Segmentation of the Left Ventricle in Cardiac Magnetic Resonance*. PhD thesis, 07 2017.

[4] Tom De Keyser Tina Tina Smets. Active shape model implementation for dental radiographs.