Fully automated segmentation of Long-Axis MRI Strain-Encoded (SENC) Images using Active Shape Model (ASM)

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Introduction: Myocardial strain is an important measure used for assessing regional function, which could help in detecting myocardial infarction and in following up patients with heart diseases. MRI Strain-Encoding technique (SENC) [1] produces strain values during the cardiac cycle. SENC proved to be one of few techniques that can quantify right ventricle (RV) regional function [2]; however, SENC images suffer from low signal-to-noise ratio (SNR). Here we present a fully automatic way to detect, segment, and track the myocardium throughout the cardiac cycle using prior knowledge of the shape of the 4-champers long-axis (LA) view.

Algorithm: Our Algorithm mainly depends on the active shape model (ASM) originally presented by Cootes et al[3] to encode the prior knowledge of the myocardium shape. We build up a myocardium model using 4 chamber long-axis SENC images of 6 controls. For each set of image, we manually segmented 2 frames (end systole and end diastole) using 35 control points: 24 points for LV and septum, 11pts for RV (see figure1). Following [3], we align and scale the shapes, then calculate the mean shape $\overline{X} = \frac{1}{N}\sum_{i=1}^{N} x_i$ (see figure 1). We calculate the eigenvectors P and eigenvalues λ of the covariance matrix, and keep only the largest eigenvectors corresponding to 90% of the total eigenvalues. This enables us to construct the allowable shapes by $X = \overline{X} + Pb$, where b is a vector of weights bounded by $-3\sqrt{\lambda_k} \leq b_k \leq 3\sqrt{\lambda_k}$ (see figure 2). For a given new set of images with multiple cardiac phases we perform two steps:

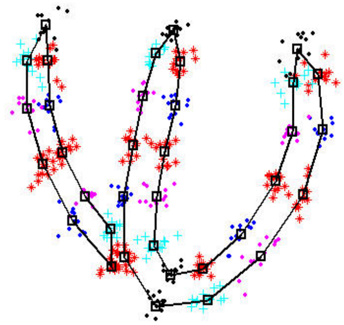

Figure 1: mean shape in black with 35 control points. Scattered points from 6 training data are scattered around each control points in different color.

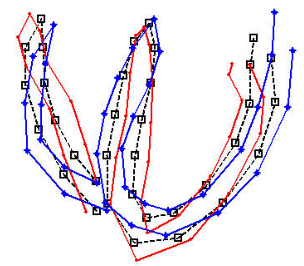

Figure 2: mean shape (doted black), mean shape + first eigenvector (red), mean shape - first eigenvector (blue)

1. Detect an approximate location of the myocardium

Here, we encode all the spatial and temporal and functional information (Strain obtained from SENC) into one image called the ACC image by:

- i- Converting each cardiac phase to a binary image by performing opening by reconstruction with a disk of radius 3, then a 50% threshold.
- ii- Obtain the ACC image by adding all the binary images.
- iii- Calculate the average strain and standard deviation through time. Pixels having average strain less than 5% or SD < 5% are set to zero in the ACC image.

This ACC image represents the average location of the myocardium though out the phases. In order to determine the location of the myocardium, we do a simple correlation between the ACC image and different scales and orientations of the myocardium mask. The myocardium mask is constructed by setting +1 to the myocardium, -1 to inner blood pool of $\overline{X}$ and it's variations. To speed up the correlation step, we down sample both the ACC image and the mask by a factor of 3, we also use large increments in scale and rotational angle.

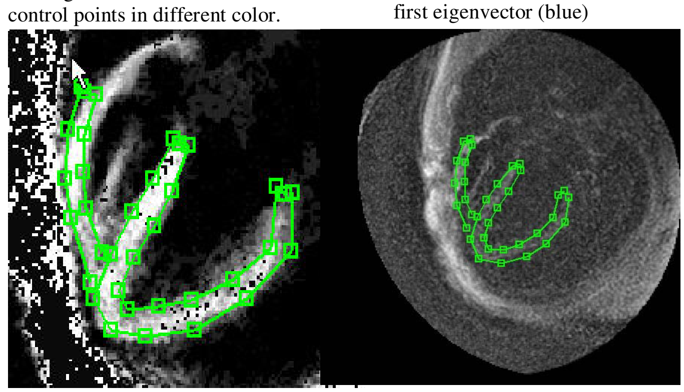

Figure 3: Acc image with mean shape converged to myocardium (left), position of mean shape on original SENC image (right).

2. Deforming mean shape using ACC image then track myocardium using SENC images

Following [3], we initialize the ASM to the approximate location obtained from step1 to deform to this particular myocardium shape represented in ACC image (figure 3-left). This new shape is then used a starting initial shape on each SENC image to track the myocardium through out each cardiac phase (figure 3-right). Note that larger convergence tolerance is used in deforming step, than in tracking phase as we expect small changes between each cardiac phase.

S	LV-SEP	RV
AVG	0.842	0.565
SD	0.029	0.216
Min	0.77	0. 12
Max	0.9	0.79

Table1: similarity values for two segments (left ventricle-septum and right ventricle)

Results: We tested our algorithm on 24 patients each containing 20-30 cardiac phases. We manually segmented all the cases in each cardiac phase and compared our segmentation with the manual segmentation using the Similarity coefficient S (equation 1) which indicates good similarity for values greater than 0.7. Table 1 shows the average similarity coefficient calculated for two segments: left ventricle-Septum (LV-SEP) and right ventricle (RV). We point out that only 5 images had S(RV)<0.3 while the rest had S(RV)>0.5.

$$S = \frac{2\left|A \cap B\right|}{\left|A\right| + \left|B\right|}$$ ---(1) where A,B are areas of automatic and manual segmentation.

Conclusion: Active shape models can successfully locate and track the myocardium in noisy SENC images allowing radiologist to calculate strain curves for different myocardium regions immediately after acquiring the images with out any human assistance.

References:

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[3] Cootes el al: Active Shape Models-Their Training and Application. Computer vision and image understanding 61:1 p38-59 (1995)

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