Automated Segmentation of Cardiac Magnetic Resonance Images

M. B. Stegmann[1], J. C. Nilsson[2], B. A. Grønning[2]

[1]Informatics and Mathematical Modelling, Technical University of Denmark, Richard Petersens Plads, Building 321, DK-2800 Lyngby, Denmark
[2]Danish Research Centre of Magnetic Resonance, H:S Hvidovre Hospital, Kettegård Allé 30, DK-2650 Hvidovre, Denmark

Introduction

Magnetic resonance imaging (MRI) has been shown to be an accurate and precise technique for assessing cardiac volumes and function in a non-invasive manner, and is generally considered the current gold standard for cardiac imaging [1]. However, assessments require manual tracings of the left-ventricular endocardial and epicardial borders and are as such very laborious. The current study represents an attempt to automate this segmentation process by using statistical models, namely the Active Appearance Models (AAMs) [2].

Data

In the current study, 14 spatially corresponding short axis end-diastolic MRIs were selected from 14 individuals. The chosen slice position represented low morphologic complexity and high contrast. The images were acquired over 15 heart cycles using an ECG-triggered breath-hold fast low angle shot (FLASH) cinematographic pulse sequence. Slice thickness=10 mm; field of view=263x350 mm; matrix 256x256. The left ventricle were annotated manually by placing 33 landmark points along both the endocardial and epicardial contours.
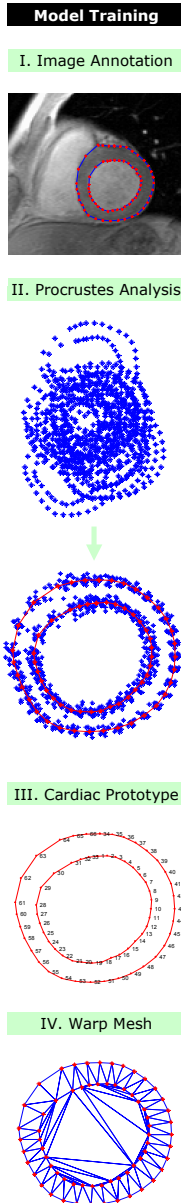
Methods

In this section, the outline of the AAM method is presented. For details, refer to [3, 4].

AAMs are elegantly capable of learning both shape and texture (appearance) variability from examples simultaneously. The major steps in the analysis are listed below and a pictorial walk-through is shown to the left:

Model Training

I. A set of representative images is chosen and annotated by experts.

II. The resulting shapes are spatially aligned using a Procrustes Analysis.

III. A mean shape is estimated and used as a shape prototype, against which all comparisons are made.

IV. Appearance variation is collected in a consistent manner, by establishing a warp function between the prototype and each training example.

V. In order to derive a specific and compact representation of the biological shape (landmarks) and appearance (pixels) variation, a principal component analysis (PCA) is performed on the aligned training set.

VI. The compact parameterisation can then be used to generate synthetic images of the object in question (e.g. the left ventricle).

Segmentation

I. The model is automatically placed in an initial configuration over the unseen image.

II. Using a principal component multivariate linear regression model, new images are generated to fit the unseen image in the best possible way. If the process converges with a satisfactory result, a match (e.g. of the left ventricle) is declared.

Model Training

I. Image Annotation

II. Procrustes Analysis

III. Cardiac Prototype

IV. Warp Mesh

Short Summary

This study demonstrates that fully automated segmentation can be accomplished in short-axis cardiac MRI using statistical image analysis. The method was evaluated in 14 individuals using an ECG-triggered breath-hold fast low angle shot (FLASH) cinematographic pulse sequence.
The left ventricle was segmented with an accuracy of 1.06 (±0.56) pixels. Ventricle areas were estimated with an accuracy of 55.0 (±40.5) square pixels (endocardial area) and 87.7 (±102.2) square pixels (epicardial area).

Results

AAMs were built on the set of 14 slices using a leave-one-out scheme, thus leading to 14 evaluations. Consequently, each model consisted of 13 examples leaving one annotation (ground truth) to compare against. Each model consisted of approx. 2200 pixels in the texture model and 66 points in the shape model. More than 95% of the combined variation (texture and shape) was explained using 10 model parameters. The mean landmark accuracy of all 14 leave-one-out evaluations was 1.06 (±0.56) pixels, calculated as mean distance to the associated border [4]. Ventricle areas were estimated with an accuracy of 55.0 (±40.5) square pixels (endocardial area) and 87.7 (±102.2) square pixels (epicardial area). Endocardial and epicardial area estimates are given figure 1. Example segmentation results are given in figure 2.
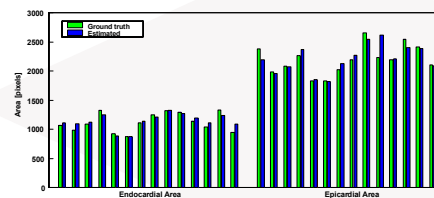

Figure 1. Endocardial and epicardial area results.

Conclusion

It has been shown that statistical image analysis can be successfully applied to 2D cardiac MRI with low morphologic complexity and high contrast. An initialisation technique has been designed which yielded a fully automated localisation of the left ventricle. Refinement of the model fit using simulated annealing optimisation, resulted in a mean landmark accuracy of 1.06 (±0.56) pixels.
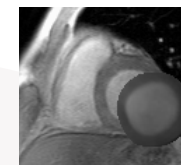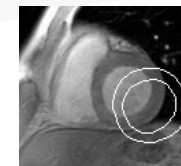
Contact Information

mbs@imm.dtu.dk, http://www.imm.dtu.dk/~aam/

V. PCA Parameters
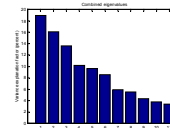
Segmentation

I. Initialisation
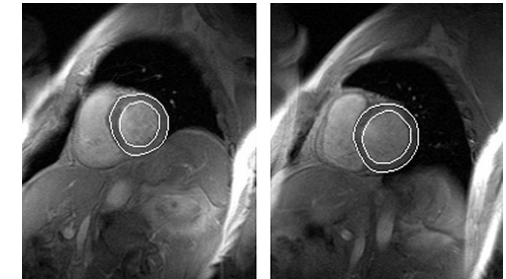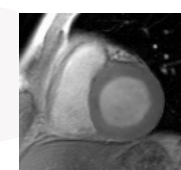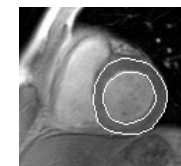

II. Search Result

Figure 2. Examples of automated segmentation of the left ventricle in short-axis cardiac MRI.
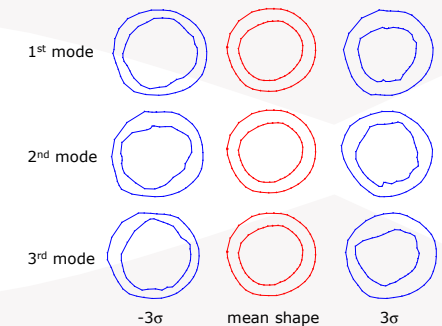

Figure 3. The first three PCA modes of cardiac variation corresponding to the fifth step in the model training.

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