4D Endocardial Segmentation using Spatio-temporal Appearance Models and Level Sets

Karl Fritscher[1], Rainer Schubert[1]

[1]Institute for Biomedical Image Analysis,
University for Health Sciences, Medical Informatics and Technology, Hall in Tirol
karl.fritscher@umit.at

Abstract. In this paper a framework for the segmentation of cardiac MR image sequences using spatio-temporal appearance models is presented. The method splits the 4D space into 2 separate subspaces, one for changes in appearance and one subspace for changes in motion. Using the 4D appearance models in combination with a level set framework combines the robustness of model based segmentation with the flexibility of level sets. The method is tested on the first two time frames of 10 cardiac MR sequences leading to promising results. Further tests using a larger training set for the segmentation of the whole cardiac cycle shall be performed in the near future.

1 Introduction

During the last years advances in the development of magnetic resonance imaging (MRI) have enabled the acquisition of cardiac 4D image sequences. These sequences can be very valuable for the treatment and early diagnosis of cardiovascular diseases. On the other hand the amount of data to be interpreted by clinicians drastically increases. Therefore methods and algorithms for the automatic and objective segmentation of 4D image sequences become increasingly important. Especially for the heart a number of approaches for volumetric modeling have been developed [1]. Most of these approaches use statistical shape models (e.g. Active Shape Models) of the heart ventricles. Some approaches have been proposed for the creation of 3D appearance models of the heart especially for segmentation [2, 3, 4, 5]. In [6, 7] and [8] 4D shape models of the right and left ventricle for the segmentation of the chambers of the heart have been introduced. In this work we propose a method for the segmentation of the ventricles and atria of the heart by using a spatio-temporal (4D) appearance model in combination with a level sets framework. The main contributions of this work are the combination of a 3D appearance model with a motion-model of the cardiac movement of the whole heart and the integration of these models in a maximum a posteriori level set framework.

2 Methods

For the creation of 3D appearance models, correspondences are achieved by finding an optimal transformation T_i: x $\rightarrow x'$, which maps a point x of the reference subject Sr onto the corresponding point x' of another subject S_i. The transformation T_{spatial} consists of a global rigid transformation T_{global} and a local nonrigid transformation T_{local}:

$$T_{\text{spatial}}(x) = T_{\text{global}}(x) + T_{\text{local}}(x) \tag{1}$$

For global rigid alignment, a signed distance map of an atlas subject S_r, on which the signed distance map representations of all other subjects S_i are mapped, is used as reference image. For the work presented herein the reference subject S_r was chosen arbitrarily. In order to compensate local differences in shape, diffeomorphic demons registration introduced by Vercauteren [9] was used. A statistical appearance model using the joint shape-intensity pair can then be computed using principal component analysis (PCA) [4]. For the creation of the motion model each point of a new image sequence $I(x, y, z, t)$ is mapped to its corresponding point in a reference sequence $I'(x', y', z', t')$ using the global part of the transformation T_{spatial} acquired from the 3D registration. Unlike Perperidis proposed in [6] proposed, this transformation is calculated individually for each time frame. Analogously each point of image $I_t(x, y, z)$ of time frame t of a sequence is mapped to its corresponding point in the reference image $I_{t+1}(x, y, z)$ of time frame t+1 of the same sequence resulting in n temporal transformations T_{temp}. Using the local part of the transformation T_{spatial} the temporal deformations are mapped onto the shape of the reference subject. This set of transformed motion fields can then be used for the creation of a statistical motion model using PCA. By performing the division of the space of cardiac shapes in two subspaces, an individual motion pattern can be applied to any joint shape-intensity instance caused by inter subject variability. Figure 1 is illustrating this pipeline. Using an adaption of the MAP level set framework described in [4] this spatio-temporal appearance model can be used for cardiac 4D segmentation.

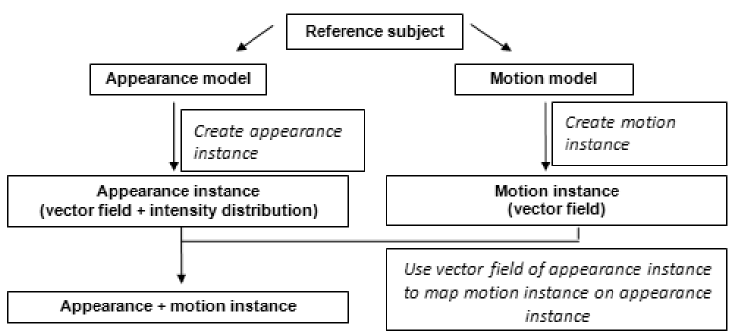
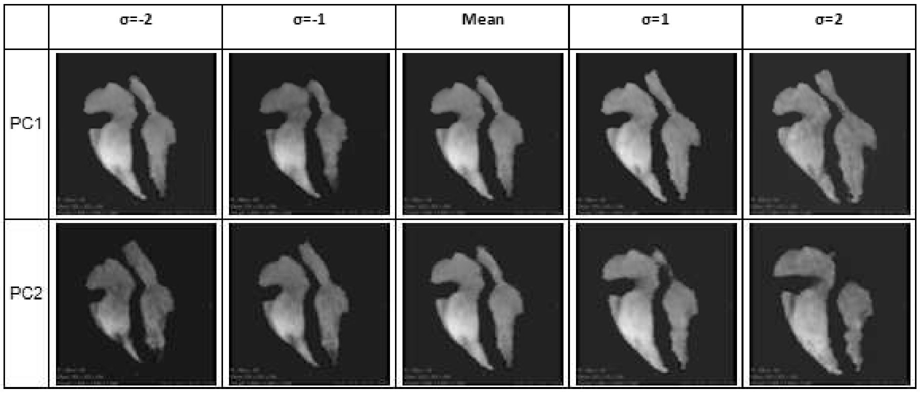


Fig. 1. Pipeline to create appearance-motion instance

Fig. 2. Significant modes of variation of the endocardial appearance (coronal cut)



3 Results

In a first test scenario the approach described in Section 2 has been applied using the first 2 time frames of 10 cardiac MR sequences with an initial resolution of 1.56mm^3. The images for the time frames are acquired 0 ms and 100ms after the R peak of the ECG. The appearance for the first time frame and the motion of the endocardium between these two time frames was modeled. Figure 2 shows the first 2 modes of variation of the endocardial appearance within 2 standard deviations (represented by one coronal slice of the 3D volume). The time frames have not been corrected in the temporal domain regarding different pulse rates. However, all the patients roughly had the same pulse rates and the differences in the first time frames can be assumed to be rather low.

Figure 3 shows the first 2 modes of variation of the endocardial motion (respectively the shapes of the blood pool enclosed by the endocardium in time frame 2) within 2 standard deviations. The different grey levels illustrate the

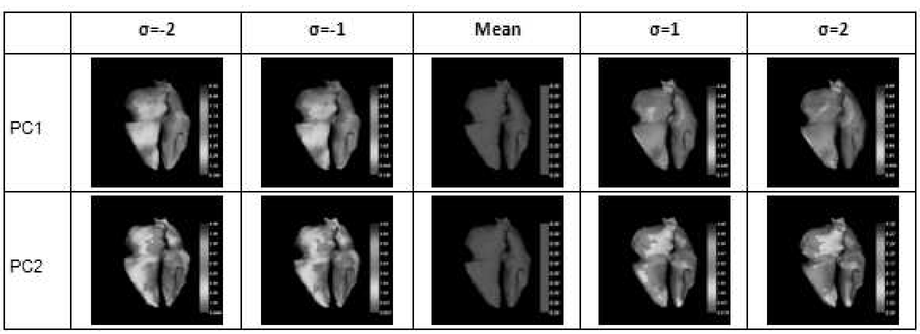


Fig. 3. Significant modes of variation for the endocardial motion

Table 1. Results of automatic segmentation compared to manual labels

Dataset	1	2	3	4	5	6	7	8	9	10
SI	0.93	0.93	0.92	0.95	0.93	0.94	0.93	0.94	0.90	0.95
HD(mm)	8.7	9.9	12.5	8.0	9.9	9.6	9.4	9.9	12.6	12.6
MD(mm)	0.96	0.93	0.93	0.7	1.0	0.84	1.00	0.90	1.28	0.89

distance to the corresponding point on the average shape of the endocardium in time frame 2. The opaque surface is representing the mean shape of the endocardium in time frame 2.

For the evaluation of the segmentation process leave all in tests for all 10 sequences using the 7 first modes of both models (covering more than 90 percent of the appearance and motion variations) have been performed. The results of the automatic segmentation were compared with manual expert segmentation of the endocardium by calculating the undirected Hausdorff distance (HD), mean distance (MD) and a similarity index (SI) between the corresponding labels. Table 1 is summing up the results of these calculations.

Note that the largest segmentation faults are situated in the area of the left atrial ear, a small processus in the left atrium. However, the average segmentation fault between the two surfaces is only between 0.75 and 1.29 mm, which is less than one pixel (pixel spacing 1.56 mm). Figure 4 is showing the result of an automatic segmentation for the first 2 time frames compared to the manual segmentation. The circle is illustrating the area of the left atrial ear.

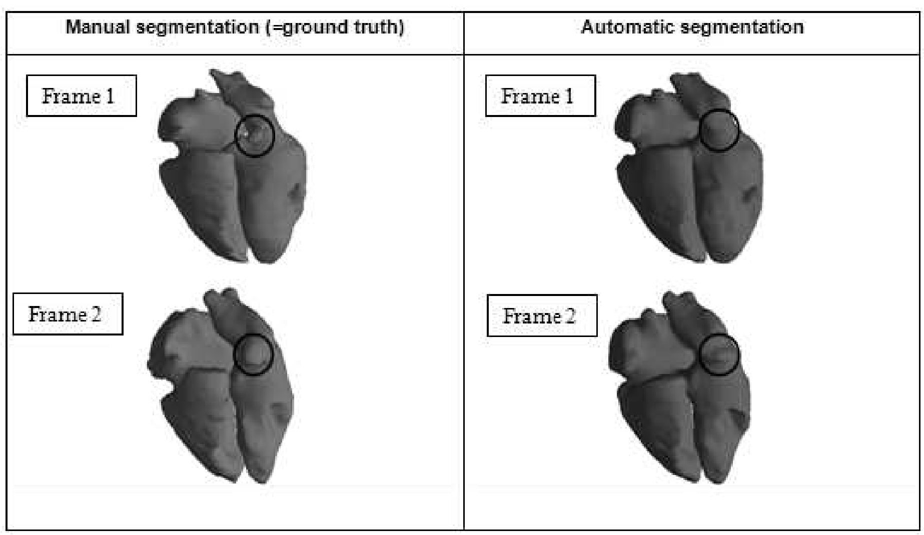


Fig. 4. Comparison of manually corrected semi-automatic (left) and automatic (right) segmentation of the endocardium

4 Discussion

In this paper we presented a novel method for the segmentation of 4D MR sequences of the heart using spatio-temporal appearance models and level sets. Compared to the usage of 4D shape models as presented in [6, 7] and [8] the usage of appearance model offers the possibility to use information about the spatial intensity distribution of an organ in order to find a proper model instance for an unseen dataset. Using segmented labels for the training set, the modeling process as well as the segmentation itself can be performed unsupervised. In first test using the first two time frames of 10 MR sequences the spatio-temporal model turned out to be adequate to model the characteristic variations concerning the appearance and motion within the training set. Moreover, the model lead to satisfying results when used for 4D segmentation. Note, however, that the size of the training set, especially for modeling the cardiac motion is extremely small and the results for the segmentation are expected to be even better when using a larger training set. This is especially true, when segmenting new unseen images. Therefore one necessary step for further improvements and more sophisticated testing scenarios would be a larger training set. Moreover, especially for modeling the endocardial motion, non-linear alternatives to PCA like LLE or kernel PCA should be tested. Moreover, all these methods will be tested for the whole cardiac cycle and with compensation of variation of individual pulse rates.

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