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# Simultaneous level set interpolation and segmentation of short- and long-axis MRI

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**Abstract**

The use of long-axis images in cardiac MRI segmentation is essential in order to locate the valves and delineate the ventricles' volume accurately. However, depending on the imaging protocol used, long-axis images do not always provide enough support for straightforward segmentation. We show that it is possible to use both short-axis and long-axis images for segmentation, even in cases where the long-axis images do not cover the entire heart volume and have various orientations and spacings, and different gains and contrasts. We propose a method to achieve this goal, based on the simultaneous interpolation and segmentation of the data in a level set framework. Results on both synthetic and real images are presented.

# 1 Introduction

Automatic segmentation of cardiac MRI images has been extensively studied over the last decade and more, thanks to its clinical usefulness. In particular, the evaluation of the volumes of the heart ventricles is a challenging problem because of the high precision required to reliably compute stroke volumes, ejection fractions, and other clinical parameters. One of the major problems in computing these volumes comes from the difficult localisation of the valves which separate the ventricles from the atrias, and thus delineate the ventricles' volumes. Indeed, these valves are generally not visible in short-axis (SA) images, which are most often used in cardiac MRI segmentation. A commonly used method to overcome this difficulty is to constrain the ventricles segmentation with a statistical model. The extra robustness provided by the model is expected to allow the demarcation of the volumes correctly without searching for the valves. However, since the valves are more easily visible in long-axis (LA) images, it would also be sensible to use these images in order to locate, or even track, the valves. In addition, the use of LA images offers the added advantage of providing a better definition of the shape of the apex.

In practise, LA images are rarely used, and the segmentation is generally performed on a stack of SA images only. This is mainly due to the fact that it is relatively easy to build a 3D volume from a set of parallel SA slices, either by using directly one slice per pixel plane or by using interpolation to fill the gaps between the slices, such as in [2, 7, 12]. However, the reconstruction of the chest volume using both SA and LA slices may be more problematic, especially when LA slices offer only a very partial cover of the chest volume and present various orientations and irregular spacings. In addition, some data sets present differences in the gain and contrast of their slices, which complicates the volume reconstruction even more. A few attempts have been made to use both SA and LA images in order to segment the heart by fitting a model on the images ([1, 4, 5, 9, 11, 12]). In [1, 4] two volumes are built from the SA and LA images separately using interpolation. Then a model of the heart is registered on the two volumes successively until convergence. In [12] a 3D volume is reconstructed by fusion of the interpolated SA and LA volumes, and a model is fitted directly on the full volume. Note that in these three cases, the authors have been able to reconstruct a 3D volume using the LA images because they had a stack of parallel and regularly spaced LA images which covered the entire heart volume. Moreover, the SA and LA slices had similar gains and contrasts. In [5, 9, 11] a model is registered on the SA and LA images without filling the gaps between the slices by interpolation, relying on the model properties to assure the continuity and smoothness of the interpolated object. In [5] the model is deformed manually, while in [9, 11] ASM and AAM methods are used.

In this paper, we present a new method to segment a 3D volume when only slices with arbitrary spatial configurations and different gains and contrasts are available. Our method relies on the use of level sets in order to interpolate data between the slices, and therefore it does not require a training phase, unlike the deformable model methods presented in [9, 11]. The rest of the paper is organized as follows. The proposed method is described in Section 2. Results on both synthetic and real images, and their analysis, are presented in Section 3. Section 4 concludes the paper.

## 2 Proposed Method

In [3], Grevera and Udupa introduced a shape-based interpolation method to reconstruct full volumes from grey-level slices. The basic idea of their approach was to preserve the shape of the interpolated objects by performing a contour interpolation of a $(N+1)$-D shape derived from the $N$-D objects, as illustrated in Figure 1. First a binary image of dimension $N+1$ is built from an original grey-level image of dimension $N$, using the grey level values of the original image to derive the additional dimension. This transformation is illustrated in Fig. 1(a). More formally, the values of the new $(N+1)$-D image are computed by:

$$f_B(v_1, v_2, ..., v_N, m) = 1 \text{ iff } f(v_1, v_2, ..., v_N) \geqslant m, \text{ otherwise } f_L(v_1, v_2, ..., v_N, m) = 0, \quad (1)$$

where $m$ is the grey value. This produces a single object (the black area in Fig. 1(a)) with a closed contour. In a second step, this contour is interpolated using implicit function interpolation. A distance function to the contour is computed, with positive values inside the object and negative values outside. Then this function is interpolated using a classic, scalar data interpolation method, and the interpolated contour is extracted from its 0-level (the red line in Fig. 1(b)). The last step consists of creating the final $N$-D image by collapsing the binary data set obtained at step 2, using the inverse process of the initial binarization (Fig. 1(c)).

This method works well on slices having the same gain and contrast. However, if that is not the case, interpolation artifacts are produced and may bias the volume segmentation. We now propose a method to interpolate the shape being segmented in a process similar to the shape-based interpolation, but which does not suffer from this limitation.

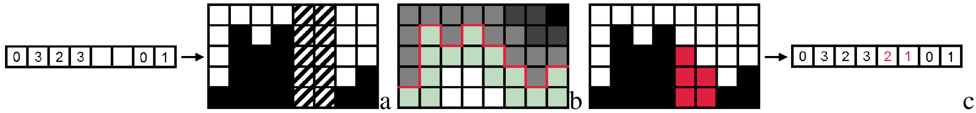



Figure 1: Shape based interpolation (1D case) - a) Step 1: Binarization; b) Step 2: Implicit function interpolation; c) Step 3: Collapsing

In order to avoid creating interpolation artifacts, we propose to interpolate the data directly during the segmentation process. In [6], Morigi and Sgallari note that Grevera and Udupa's shape-based interpolation is the same as interpolating every greylevel line (i.e. iso-intensity contour lines) in the volume using distance transform interpolations. Furthermore, they propose to use level sets, which are distance functions, to perform the interpolation. They use level set morphings in order to generate missing slices between parallel ones. This method can not be used with slices having arbitrary orientation, and would not remove the interpolation artifacts produced by different gains and contrasts of the slices. However, we propose to interpolate the missing data by interpolating the level set function itself during the segmentation process. Therefore, instead of interpolating every greylevel line, we interpolate only the shape being segmented, which generally corresponds to a greylevel line. The complete algorithm is then as follows: At each iteration,

1. Evolve the level set function in the image planes, that is to say where data support is available to compute the velocity of the contour.

2. Interpolate the level set function between the image planes.

The level set's velocity is computed locally in the individual image planes, so the evolution of the contour is not sensitive to differences in the gain and contrast of the slices. Consequently, the object's shape is correctly segmented in the image planes and interpolated outside.

We experimented with two methods to interpolate the level set function, namely natural neighbours (NN) interpolation and curvature based interpolation. NN interpolation was introduced by Sibson in [8]. In order to interpolate a point $\mathbf{x}$, this method relies on a Voronoi diagram to find the coordinates and weights of the interpolating neighbours $P_i$. The weight of each neighbour $P_i$ is computed directly from the volume of the Voronoi sub-cell that point $\mathbf{x}$ would "steal" from it if it was inserted into the Voronoi diagram.

We note that interpolating the level set function is the same as smoothing it. This observation provides us with the second level set interpolation method, which is a simple smoothing of the level set function under the influence of its curvature, i.e.:

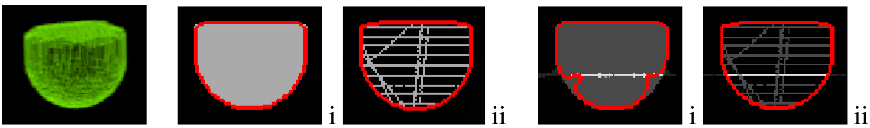
$$\frac{\partial \phi(x)}{\partial t} = \kappa(x)\left|\nabla \phi(x)\right| \tag{2}$$

Here $\phi(x)$ denotes the level set function and $\kappa(x)$ its curvature at point $x$. This method provides a better smoothing of the level set function than the NN method, and is considerably faster.

# 3 Results

We tested the proposed method on synthetic and real data sets, against the shape-based volume reconstruction method of Grevera and Udupa [3]. Two synthetic data sets were used in this study. They consist of a 3D volume containing an object made of a cylinder and a hemisphere (Fig. 2(a)). In the first data set, all the slices have the same gain and contrast (Fig. 2(b)), while in the second set one slice has been given a different gain and contrast (Fig. 2(c)). The volume in each of the two data sets is the typical size of a real one, and the position and orientation of the slices are the same as SA and LA slices of a real data set chosen arbitrarily.

We used the CACE level set algorithm introduced in [10]. The volume reconstruction method and the proposed method gave similar results when tested on the first data set (Figure 2 (b)). The computed Jaccard's coefficients are 97.6% when segmenting the original, full volume data set, 96.6% after reconstructing the volume using the shape-based interpolation method, and 92.7% with the proposed method. The two methods gave very different results when tested on the second data set, and the propose method achieved a better accuracy. Indeed, with the shape-based volume reconstruction method, the interpolation artifact disturbs the evolution of the level set and attracts the contour like an object's border (Fig. 2(c)i), and the resulting Jaccard's coefficient is only 85.9%. However, the proposed method did not create such artefacts and was able to contour the object correctly, yielding a Jaccard's coefficient of 93.0% (Figure 2(c)ii).




(a) (b) (c)

Figure 2: Segmentation of synthetic data sets; (a) Full volume data set, (b) Homogeneous data set, (c) Data set with different gains and contrasts; in each case (i) is the Shape based interpolation method and (ii) is the proposed method (xz-plane in the middle of the volume (long-axis view))

Our real data comprises of 10 data sets, each containing 11 parallel SA images spaced by 10mm, and 3 to 6 LA images with various positions and orientations. The pixels in the data sets range in size from 1.7708x1.7708mm to 2.0833x2.0833mm. In Fig. 3, we show a comparative result where our proposed approach is more accurate while the shape-based interpolation method suffers through the introduction of interpolation artifacts which attract the active contour to incorrect positions. Additionally, our method is faster, with a processing time of 7.4 minutes against 15.1 minutes for the shape-based interpolation method - using C++ under Linux on a 3GHz CPU with 3.8GB RAM.

# 4 Conclusion

We proposed a new method to interpolate and segment 3D data from SA and LA cardiac MR images simultaneously. The approach is suited to any data set, regardless of the spatial configuration, and gain and contrast, of the slices. This is achieved through the interpolation of the level set function itself rather than the images. The method was tested against a shape-

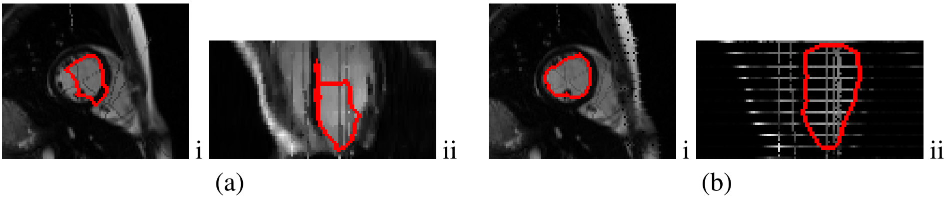



Figure 3: Segmentation of a real data set; (a) Shape-based interpolation method, (b) Proposed method; i) One short-axis view, ii) xz-plane in the middle of the volume (long-axis view)

based volume reconstruction method, on both synthetic and real data sets. The two methods gave similar results on data sets made of slices having the same gains and contrasts, but the proposed method was superior on all other data sets.

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