Segmentation of MR images with B-spline snakes: A multi-resolution approach using the distance transformation for model forces

T. Stammberger[1,2], S. Rudert[1], M. Michaelis[3], M. Reiser[2], K.-H. Englmeier[1]

[1] GSF - Institut für Medizinische Informatik und Systemforschung, Ingolstädter Landstr. 1, 85764 Oberschleißheim, Germany
Email: stamm@gsf.de
[2] Institut für Radiologische Diagnostik, LMU, 81377 München
[3] Plettac Electronics, 90766 Fürth

Abstract A B-spline snake algorithm is proposed for the segmentation of the knee joint cartilage from MR images. A first guess of the contour is provided interactively and is transformed into a B-spline representation. Image forces attract the B-spline curve towards the real cartilage boundaries. In addition, model forces based on a distance transformation are introduced in order to guide the evolution of the contour in those parts of the image that show no significant features. The total energy of the B-spline curve is minimized within a multiple scale approach. The algorithm turned out to be more accurate as the manual delineation of cartilage boundaries from medical experts.

Keywords: segmentation, deformable contours, B-spline snakes, MR imaging, cartilage

1 Introduction

Many quantitative medical image analysis applications, like the measurement of anatomical structures, require prior segmentation of the organ from the surrounding tissue. Our special interest is the segmentation of the knee joint cartilage from magnetic resonance images (MR) for 3D visualization [1], volume and thickness measurements [2, 3], and tracking of the cartilage surfaces in compression experiments [4].

Since the manual delineation of the cartilage boundaries is tedious and time consuming, a lot of effort has been devoted to automate this processing step [5]. The seminal work of Kass et al. [6] inspired many promising approaches to find boundaries in medical images by the use of deformable contour models [7] or B-spline snakes [8, 9]. Both concepts have proven to be suitable for matching an initial contour to smooth object boundaries in noisy images such as the cartilage in MR images. These boundaries can *not* be detected by simple low level features like edges alone. The power of the method lies in the combination of *external image forces* that are based on low level features and attract the initial contour towards the object boundaries, and of *internal forces* that preserve the shape of the contour. In the B-spline snakes approach no explicit internal energy term is required since the B-spline represantation implies the smoothness of the contour.

In addition to the external image forces, we have introduced so-called *model forces* that measure the similarity of the contour to a given model using the Euclidean distance transformation (EDT) [10, 3]. In contrast to other model based approaches [5] where the movements of the contour are restricted within fixed limits implied by the model, the EDT permits to influence and guide the adaption process of the contour in a continuous and smooth way. The initial contour is either provided by user interaction or another initial guess taken for instance from a training set or a geometric model of the cartilage.

In this work we propose an energy-minimizing deformable contour algorithm for the segmentation of the cartilage from MR images. 3D segmentation is achieved by subsequently projecting the 2D contours to the following image slice. The performance of the algorithm is compared to manual segmentation from experienced physicians.

2 Segmentation method

The first step of the segmentation process is the transformation of the initial contour into a B-spline representation. Then the external image and model energy associated with the B-spline curve is minimized subsequently on different filter scales.

2.1 B-spline contour representation (internal energy)

A B-spline of order k is a C^{k-2} continuous parametric curve that depends only on a number of *control points* $\boldsymbol{v}_1, \ldots, \boldsymbol{v}_N \in \mathbb{R}^2$. The B-spline curve is defined as

$$\boldsymbol{x}(u) = \sum_{i=1}^{N} \boldsymbol{v}_i B_i^k(u) \tag{1}$$

where $B_i^k(u)$ are the polynomial *blending functions* (of order k), u is the curve parameter and $\boldsymbol{x}(u) = (x(u), y(u))$ [11].

Due to the following properties B-spline curves are an appropriate curve representation for deformable contour segmentation: (i) The smoothness of the curve corresponding to the internal energy of the contour can be adjusted by the number of control points. (ii) The blending functions $B_i^k(u)$ have only local support, i.e. varying the position of one control point only affects a small part of the curve.

In our algorithm the initial contour is transformed into a B-spline representation by sampling the contour with regard to a curvature measure in a way that the more a curve segment varies the more control points are inserted up to a user defined maximal number. These sampled contour points are taken as control points that are iteratively adjusted until the B-spline fits the initial contour.

2.2 External energy

There are two external forces in this algorithm: image forces E_I, and model forces E_M. The total energy E is then given as a weighted sum of the image and model forces $E = \alpha E_I + (1 - \alpha) E_M$ where α is a heuristic parameter depending on the object to be segmented and the image contrast.

Image forces The contour is attracted to the edges of the object that are measured by the gradient of the image intensity $I(x,y)$. We estimate the strength of the gradient $\|\nabla I(x,y)\| = \sqrt{I_x^2 + I_y^2}$ by convolving the image data with Gaussian derivative filters $I_x(x,y) = I * g_x$ and $I_y(x,y) = I * g_y$ with $g_x(x,y) = -\frac{x}{2\pi\sigma^4} e^{-\frac{x^2+y^2}{2\sigma^2}}$, etc., where σ is the scale of the filter [12]. Then the gradient magnitude is integrated along the B-spline curve yielding a measure E_I how well the contour fits to the image evidence (L is the length of the curve):

$$E_I = -\frac{1}{L} \int_u \|\nabla I(x(u), y(u))\| du \tag{2}$$

Model forces We introduce a model energy to force the contour to be in accordance with a model of the object geometry. This is particularly important in images or image regions with no significant edges. The model can either result from a training set, an analytical object description, or - as in our case - from an initial guess provided by the user.

A distance map $D(x,y)$ of the model boundary is created [10, 3] assigning to every pixel of the map the Euclidean distance to the closest boundary point. The energy E_M is then defined as the sum of the distance values in the map along the B-spline curve:

$$E_M = \frac{1}{L} \int_u D(x(u), y(u)) du \tag{3}$$

This is equivalent to the mean distance between the B-spline curve and the model contour which determins the similarity of the contour with the model.

2.3 Hierarchical minimization

The B-spline curve and hence the total energy E only depends on the positions of the control points $\boldsymbol{v}_i$ ($2N$ degrees of freedom). Therefore, the problem of finding the best match of the contour with the image evidence can be stated as a minimization of the total energy over the $2N$-dimensional space of all control point configurations: $E = E(\boldsymbol{v}_1, \ldots, \boldsymbol{v}_N) \stackrel{!}{=} \text{min}$.

The minimization is performed in the scale space, starting at a corse filter scale σ and reducing the scale by a factor 2 in each step. The optimal contour of one level is taken as initial contour for the next detailed level, while minimizing the energy function on each level using the gradient descent optimization method.

2.4 Extention to 3D segmentation

The segmented boundary in one slice is used as initial contour for the following image of the 3D volume sequence thus providing a full 3D segmentation of the cartilage. This simple and straight forward approach shows still satisfying results since the shape of the cartilage does not change dramatically from slice to slice in transverse or sagittal imaging planes.

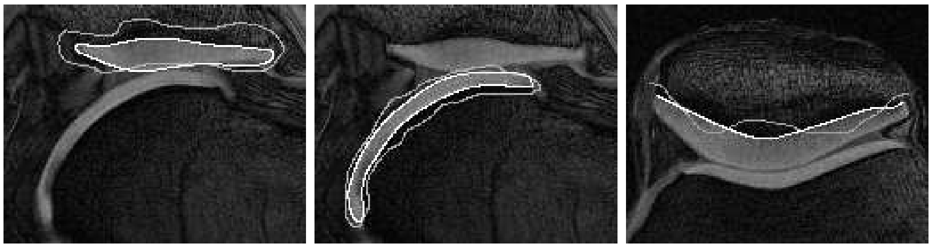

Figure1. Due to the hierarchical minimization even bad initial contours (gray lines) can be attracted to the required object (bright lines) (patella (left) and femur (middle) cartilage). The algorithm handles both open and closed contours (right: bone-catilage interface).

3 Results and discussion

The algorithm is currently employed in several clinical studies [2, 3, 4]. The correct performance is controlled visually by medical experts whereas only in few cases interaction is required to improve the segmentation results.

We compared our method to the manual segmentation of experienced physicians. The same object was segmented eight times while systematically excluding one and calculating the mean Euclidean distance to the seven remaining segmentation results. The average of theses experiments was taken as a measure giving an upper bound for the reproducibility of the segmentation method. In this way the segmentation results of eight medical experts were compared to that of our algorithm with eight randomly chosen start contours. For both, an open and a closed object boundary (Fig. 1), the snake segmentation (0.22 and 0.18 pixel) was more than twice as precise as the manual one (0.48 and 0.43 pixel). This means that the snake segmentation is is not only faster but particularly more reproducible than the manual segmentation even though it is not fully automatic.

Moreover, in comparison to feature based algorithms (e.g. region growing) that had also been tested in the scope of our clinical studies the snake approach proved to be more suitable for the segmentation of smooth objects in noisy MR images.

In practice, three filter scales σ with a minimal scale of about one pixel turns out to be a good compromise between time performance and robustness for the hierarchical minimization scheme. The largest filter scale serves for the coarse matching whereas the lowest scale permits to delineate the exact shape of the cartilage. This ensures that even if the first contour guess is far away from the cartilage boundary the snake still 'feels' the image forces since their range is limited by the filter scale (Fig. 1).

The adaption of the snake to a given model can be achieved by superimposing model forces to the image forces. In regions with insufficient image features, they prevent the contour from random movements or attraction to nearby objects (Fig. 2).

In contrast to other deformable contour approaches [5] our algorithm is able to perform the energy minimization in real-time on a SGI workstation. This

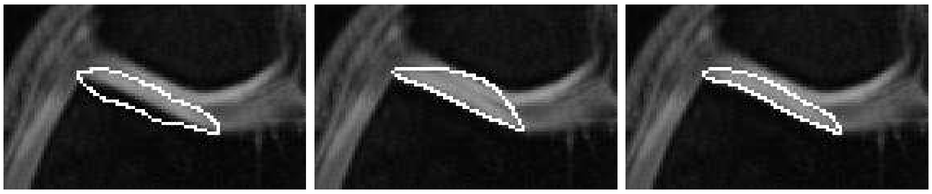

Figure2. The influence of model forces. Segmentation of the femur cartilage without (middle) and with (right) model forces starting from the same initial contour (left) (10 control points). With model forces the snake is correctly matched to the femur boundary (right).

is due to the efficient contour representation as B-spline curve. Therefore the proposed method is not only useful for a quasi-automatic segmentation procedure but also a powerful tool in assisting the interactive segmentation of a large variety of image objects.

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