Autonomous Direct 3D Segmentation of Articular Knee Cartilage

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Abstract

The aim of the work presented here, is to speed up the entire evaluation process of articular knee cartilage and the associated medication developments for Osteoarthritis. To enable this, the development of an automated direct 3D segmentation is described that incorporates non-linear diffusion for efficient image denoising. Cartilage specific magnetic resonance imaging is used, which allows acquiring the entire cartilage volume as one 3D image. The segmentation itself is based on level sets for their accuracy, stability and topological flexibility. By using this kind of segmentation, it is hoped to improve the time efficiency and accuracy for quantitative and qualitative integrity evaluation of cartilage and to enable an earlier diagnosis and treatment of Osteoarthritis.

INTRODUCTION

Osteoarthritis (OA) occurs typically in the aged with a typical age range of 30 to 70 years, occurring earlier under extreme conditions such in as high-impact sports. It is a major cause of morbidity and causes significant health costs to communities. Much of the cost is associated with the treatment of late, symptomatic disease, especially joint replacement surgery. The work described here is part of the Brisbane Osteoarthritis Imaging Study (BOIS), a collaborative study between Pfizer and the University of Queensland, whose overall purpose is to develop a Phase II OA "Proof of Concept" clinical model by assessing changes in joint structure in knee OA in high risk patient cohorts using state-of-the-art magnetic resonance imaging (MRI). A significant advantage of using MRI is that it allows the acquisition of high-contrast cartilage images.
The purpose of segmentation for BOIS is to reliably extract the structure and pathological occurrences in cartilage from MR images. This will then form a basis for the detection of OA progression, which relies on quantitative and qualitative assessment of cartilage volume and thickness measurements.

There is currently no consensus on how to assess disease progression using MRI, and studies to date have generally focussed on cartilage volumes at their endpoints and incorporated segmentation with a high level of user interaction. Here we focus on the automation of the segmentation and the improvement of the accuracy of cartilage measurements in order to streamline further analysis and to enable an earlier detection of cartilage pathologies. A sensitive registration method for cartilage changes over a longer time period (e.g.: several month) will also be developed, based on segmentation fine-tuning for smaller diurnal changes.

The expected outcomes include:

- An autonomous segmentation method:
  - Accelerated drug trials
  - Simpler pre- and post-operative disease monitoring
- Early detection of Pathology-Associated Changes (thickness and volume changes)
  - Early diagnosis
- Detection of early onset OA (eg. due to sporting injuries)

This problem has been explored previously in [1]. They found that using only grey level features for the distinction of very similar cartilage contact zones was insufficient, and introduced a segmentation method in scale space. They formulated the problem as a hierarchical energy minimisation solved using a gradient descent scheme based on B-spline snakes. The use of a hierarchical scheme was found to produce relatively robust segmentations. Their automated algorithm failed to segment the cartilage between the patella and femoral cartilage and between the femoral and tibia cartilage and, therefore, required user interaction.

The solution of these drawbacks is the main objective of this work – to develop a fully automated 3D segmentation based on a level set approach [2] and non-linear diffusion (NLD). In order to do this we will overcome the distinction problem between very similar cartilage contact zones. Therefore, we apply NLD for an efficient image simplification and level sets for their improved stability, simple 3D implementation, accuracy and topological flexibility. Additionally, multispectral image information

will be considered to provide different contrast features for the distinction of similar tissues. The use of a 3D segmentation method is expected to give improvements over traditional 2D methods and assist in the automation of the method.

This paper is organized as follows: It starts explaining Osteoarthritis and segmentation relevant cartilage properties, and shows then the cartilage lesion classification system by Outerbridge in table 1. Furthermore, it is described how to overcome cartilage-imaging problems and advantages of 3D imaging are pointed out. Then current drawbacks for segmenting articular knee cartilage are explained. Subsequently, solutions as image simplification and the application of level sets for a 3D segmentation are proposed. In the discussion and results section two images containing the same information but with different contrasts are shown and their combination for multispectral segmentation described.

OSTEOARTHRITIS AND ARTICUALR CARTILAGE IN THE KNEE

The goal of our segmentation method is to extract the femoral and tibial articular cartilage. These cover the bone endings of the tibia and femur, which are part of the knee joint. The cartilage consists of a well-organized, multi-layered structure providing a high load-bearing capacity, high compressive stiffness and a smooth surface [3]. The smoothness of the cartilage surface and the additional lubrication provided by the synovial fluid allow low-friction gliding within the knee joint. Cartilage damage increases this friction and erodes the cartilage until femur and tibia come into direct contact, causing significant pain and eventually disability. Osteoarthritis and other types of arthritis are the second leading cause of disability in the United States [4].

MULTISPECTRAL IMAGING

For an automatic segmentation, current available MRI sequences are not sufficient to provide enough contrast between similar cartilage contact zones. To overcome this disadvantage we propose imaging with two different contrasts: fat- and non-fat-suppressed sequences. It is hoped that the combination of both sequences will allow better cartilage distinction than either allows individually.

CARTILAGE LESION CLASSIFICATION SYSTEM

Cartilage lesions of the knee may be characterised using the classification system of Outerbridge [5]. Currently available imaging sequences are sufficient for detecting grades 2-4 only and sequences to enable proper detection of grade 1 are under development. In this project thickening and softening detection will be enabled by incorporating sodium 23 nuclear MR imaging.

Table 1. Cartilage lesion classification system by Outerbridge

Grade	Symptom
1	Thickening and softening
2	Fissuring of the articular surface that does not extend to the underlying bone.
3+4	High-grade lesions with partial or full-thickness cartilage defect, respectively.

3D IMAGING

Traditional studies use 2D slice-based acquisition [1]. This often requires that each slice be aligned before processing, and introduces significant anisotropy into the image data. In this project we apply 3D imaging methods for improved spatial resolution and to avoid alignment problems. Therefore, the complete knee joint image is acquired as a monolithic volume.

In this study we use a water excited 3D DESS (Dual Echo Steady State) sequence. The imaging sequence enables high contrast between normal and abnormal cartilage, both in deep and superficial layers. It displays cartilage with an optimal contrast and high spatial resolution. Furthermore, volume calculations and 3D display are facilitated. The water excitation of the sequence enables cartilage selective display, whereas all other tissues appear darker. More over it provides high-quality multiplanar reconstruction (MPR), a strong T2 contrast and an improved signal to noise ratio. Despite its cartilage selectivity, the assessment of other joint structures is also possible.

SEGMENTATION

It is hypothesized that repeating a multispectral segmentation reveals differences in separation of pathological cartilage against the menisci. Here we intend to develop a fully automated segmentation method using NLD and level sets. Articular cartilage is difficult to segment because it is a thin structure (1-2mm). Its transmitted MRI signal intensity is proportional to its size and difficult to distinguish at low spatial resolutions. The problem of tissue differentiation becomes quite challenging and the main problem of automation is the distinction between deteriorated cartilage and its similar surroundings, such as the two menisci and the synovial fluid. At the end of the deterioration process the cartilage becomes indistinguishable from noise. To improve the signal to noise ratio, non-linear diffusion will be applied prior to segmentation.

Multispectral Segmentation

Another difficulty is that the given sequences cannot be used to reliably image early cartilage degeneration. To overcome the aforementioned problems we intend to consider a combination of more distinction properties for the segmentation by using multispectral images.

Manual Segmentation

As a reference for an accuracy validation a manual segmentation is performed first. Several 2D slices are printed out and an expert draws a line manually around the cartilage contour. These manual segmentations are then digitized and may then be used as templates to validate the results of automated segmentation.

Non-Linear Diffusion

First the acquired images are cropped to the area of interest, which includes the cartilage and its surroundings. Subsequently, the image is simplified to reduce noise and remove insignificant details. A standard method for this is to convolute the image with a Gaussian kernel. The disadvantage of this method is that due to its linearity, meaningful details such as edges are removed in the same manner as less important details. To overcome this disadvantage Non-Linear Diffusion (NLD) is used here. NLD enables image simplification while preserving meaningful features such as contiguous edges. Non-linearity is given by using a spatial-varying diffusity, which adapts to the image intensity gradient. Near significant edges the diffusivity reduces to zero and while in the interior of objects the diffusivity increases, allowing selective blurring.

The convolution of an image by a Gaussian kernel G_σ smoothes the image, reducing all image details equally. The scale σ of the kernel controls the amount of smoothing. Perona and Malik [6] recognized that this may be viewed as a linear diffusion:

$$I_t = \mathrm{div}\left(c \nabla I\right) \quad (1)$$

Here the diffusivity c is constant over the image plane. For a non-linear diffusion Perona and Malik [6] introduced spatially varying diffusion coefficients, such that the diffusivity is low on intensity gradients. Strong intensity gradients are typically associated with object edges. This choice of diffusivity function not only preserves large intensity discontinuities but sharpens the edges of objects. In the non-linear case we may rewrite the first equation 1 as:

$$I_t = \mathrm{div}\left(c\left(\left|\nabla I\right|\right) \nabla I\right) \quad (2)$$

Previous Work: B-Spline snakes

Deformable contour models or snakes that are based on the seminal work of Kass et al. [7] have been proven to be suitable for matching smooth surfaces such as the cartilage contour in MR images. The advantage of these models lies in the combination of external image forces, which are based on low level features that attract the initial contour toward the object boundaries and on internal forces such as the contour elasticity that preserves the smoothness of the contour. The previous work from [1] on knee cartilage segmentation uses B-Splines and a hierarchical energy minimization approach performed in scale space. The process starts at a coarse scale and reduces the scale in each step, while minimizing the energy function on each level. To let the algorithm start at a coarse scale assists contour attraction even if the initial contour is inaccurate, and minimises the attraction to noisy edges in the surrounding tissues. These properties are responsible for the stability of this algorithm. The semi-automated segmentation enabled by this method allowed a considerably higher reproducibility compared to a manual segmentation, which motivates developing the following automated segmentation.

Algorithm Development Using 3D Level Sets

Following mathematical descriptions are based on [2].

The cartilage surface S to segment, is represented in space R^3 as:

$$S : [\delta, \tau] \rightarrow \square$$

and embedded into the three dimensional level set function ϕ that maps to one dimension R:

$$\phi : \square \quad \rightarrow \square$$

such that S becomes an isosurface of ϕ

$$\phi(S) = 0 \, .$$

Now the level set function ϕ needs to be manipulated to match the cartilage contour and is represented as a partial differential level set equation:

$$\partial \phi / \partial t = - F \left|\nabla \phi\right| .$$

The gradient magnitude $|\nabla\phi|$ is multiplied with the speed function F that describes the normal velocity of the surface S. F is responsible to guide the surface and can be defined to allow a wide range of surface deformations in order to match the cartilage contour.

Advantages of Level Sets

The advantage is to have always control over the level set function ϕ, despite possible contortions of the embedded cartilage surface S. This property enables to handle easily breaking and merging for the segmentation process. Another benefit is that the technique trivially extends to three dimensions. Also, level sets allow establishing less complicated numerical schemes to approximate motion equations. The cartilage surface S matches the zero level set of the adjustable level set function ϕ. This allows starting the evolution process with a partial differential equation that is similar to the Hamilton–Jacobi equation. These conditions ease the evaluation of normals and curvatures and topological changes occur normally.

NLD, Level Sets and 3D Advantages for Automation

As above mentioned is one monolithic image volume acquired that is stored as a series of 2D-sliced DICOM images. The second focus – besides automation – of our work is to take advantage of the volumetric and singular property of the acquired data. Therefore, the series of 2D images is first reassembled to one 3D image. Subsequently, level sets are applied, to enable a segmentation of the complete three-dimensional cartilage contour at once. Level sets are the successor of snakes and offer a better stability, accuracy and topological flexibility. It is therefore hoped too gain improvements compared to the previous work [1] that uses the snake-splines approach. In addition to that, we use NLD in the first segmentation instance to efficiently denoise the image. It is hoped that combining NLD, level sets and multispectral image information enables automated cartilage segmentation.

Time Efficiency and Accuracy Improvements

All together there are three accuracy and two time efficiency improvements to expect.

We are using only one 3D image that contains all the information about the complete cartilage structure to segment. Using the one volume gives a better resolution, since "gaps" between 2D-acquired and 2D-segmented image slices—after assembling those to a volume—are avoided. The process will be faster, because everything will be directly 3D-segmented at once, and segmenting and combining of 2D slices becomes unnecessary. The direct 3D segmentation of the complete cartilage volume in one step and the automation feature are expected to speed up the entire segmentation process.

The three accuracy improvements are based on the better accuracy of level sets themselves, on the higher resolution as previously explained and that the automation avoids subjective decisions about tissue border distinctions.

It is also aimed to design a user-friendly GUI to reduce the familiarizing time and, therefore, the post-processing time.

DISCUSSION AND RESULTS

Based on the automatic segmentation described in this paper, it is intended to speed up drug development and to eventually improve OA medication. It is also aimed for an earlier OA treatment by detection of pathology-associated changes in cartilage as early as possible. This will be based on an automatic and more accurate segmentation and on Sodium 23 nuclear MR imaging, which will be considered for detecting abnormal cartilage changes as softening and thickening.

For comparison two images with different contrasts (fat- and non-fat-suppressed) are shown below and to the right. The image in figure one was acquired using the 3D DESS sequence with water excitation. Cartilage contains with 75% significantly more water than bones (22%). Therefore, mainly cartilage is visible, whereby bones containing fat appear dark (fat-suppressed).

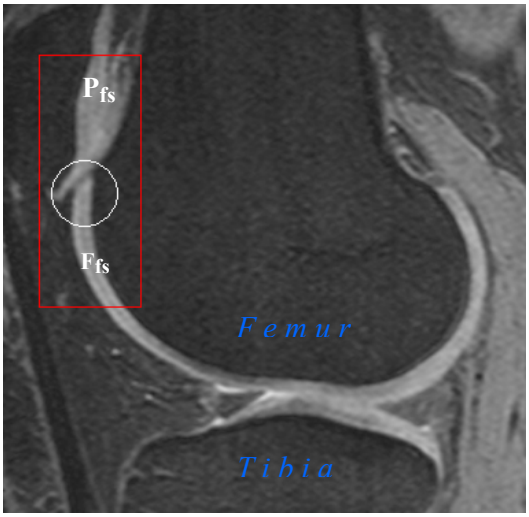

Figure 1. Knee joint in 2D view (fat– suppressed)

The image in figure two is acquired using a non-fat-suppressed sequence. Therefore, bones (containing bone marrow with fat cells) are better visualized as before. In both images P denotes cartilage belonging to the patella, F femoral cartilage and fs abbreviates fat-suppressed. The patello-femoral cartilage contact zone is within the white circle between P and F. As an example to enable better contrast, image parts around P_{fs} of figure one could be used to superpose or replace the same parts of the patella cartilage P in figure two. This would then result in a better contrast between P and F and support a distinction of both cartilage types.

The algorithm development is currently in the initial phase and more results will be provided soon.

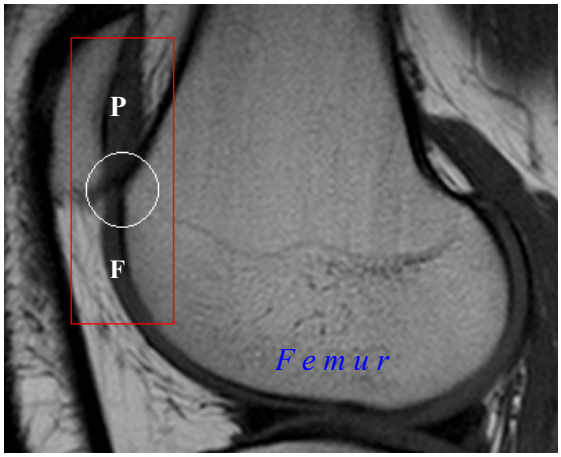

Figure 2. Knee joint (non– fat– suppressed)

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