Automatically Initialisation of 3D Deformable Models for Cartilage Segmentation

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Abstract

Deformable models are a highly accurate and flexible approach to segmenting structures in medical images. The primary drawback of deformable models is that they are sensitive to initialisation, with accurate and robust results often requiring initialisation close to the true object in the image. Automatically obtaining a good initialisation is problematic for many structures in the body. The cartilages of the knee are a thin elastic material that cover the ends of the bone, absorbing shock and allowing smooth movement. The degeneration of these cartilages characterize the progression of osteoarthritis. The state of the art in the segmentation of the cartilage are 2D semi-automated algorithms. These algorithms require significant time and supervision by a clinical expert, so the development of an automatic segmentation algorithm for the cartilages is an important clinical goal. In this paper we present an approach towards this goal that allows us to automatically providing a good initialisation for deformable models of the patella cartilage, by utilising the strong spatial relationship of the cartilage to the underlying bone.

1. Introduction

Osteoarthritis (OA) of the knee is often characterized by the degeneration of the cartilages; this degeneration usually consists of localised thinning or thickening of the cartilage that develops slowly over time. MRI has been shown to provide a more accurate way to diagnose and monitor OA compared to other imaging modalities. These studies monitored the progression of OA using measurements like thickness [1][16], volume [17] and surface area [10]. These measurements require the cartilages to be segmented in an accurate and repeatable way. Unfortunately, due to the low contrast in several areas, particularly in the joint contact areas, tendons and ligaments, fully automated segmentation of the cartilage has not been achieved.

Current clinical studies have used supervised semi-automated 2D algorithms like region growing [4], active shape models [14], active contours [12] and live wire [7]. These algorithms all require various degrees of user interaction, verification and correction of the segmentation results slice by slice. These approaches have significantly reduced the time taken to segment images and provide higher intra- and inter-observer consistency than fully manual methods. However, these approaches are too time consuming for routine clinical use, so the development of a fully automated approach is desirable.

It is our belief that the automatic segmentation of the cartilages will require the segmentation to be performed directly in 3D. There have only been a few attempts to do this, including a model based approach [11], immersion based watershed [6] and statistical classification [15]. The most promising work uses a modified watershed metric that utilises prior information to perform the segmentation of the cartilages [8]. This algorithm can be combined with an atlas registration to fully automate the segmentations; however this has yet to be performed with the cartilages.

Shape information is a significant piece of knowledge that can be used to compensate for missing or poor delineation of different tissues. It has been shown in 2D that approaches utilising shape information in segmentation algorithms like active shape models (ASMs) can produce accurate and robust results for the articular cartilage [14]. The primary problem with ASMs is, like all deformable models, they are sensitive to initialisation, and automating their initialisation is difficult.

In this paper we present a novel approach to automati-
cally provide a good initialisation for deformable models of the patella cartilage by utilising the spatial relationship of the cartilage to the underlying bone. The deformable models are represented by 3D statistical shape models (SSMs), which allows the flexible incorporation of shape information into our segmentation algorithms. This provides some constraints and guidance in areas where there is little contrast between cartilage tissues (See Figure 1), joint contact areas, tendons and ligaments. The training database for the SSMs is usually used to extract gray level appearance information for use in the segmentation process. However, other useful pieces of information like the spatial relationship between objects in the body can also be used.

The philosophy we are following in our development of a segmentation system for the cartilages of the knee is similar to the thoughts of both Kapur [11] and Hamarneh [9] and is focused on the effective but flexible incorporation of a priori knowledge, that can be utilised intelligently to aid in our goal of obtaining automated, accurate and robust segmentations of the knee cartilages.

The core of the segmentation system is the creation of a statistical map of the knee based around 3D statistical shape models (SSMs) of the bones. This allows both the inclusion of shape constraints into segmentation algorithms as well as a framework for the inclusion of other a priori knowledge. The SSMs can act as a framework to incorporate a priori knowledge by utilising the corresponding landmarks to extract information from the set of training images. This information can consist of gray level appearance, texture or even the spatial relationship between various objects. This information can then be used in segmentation algorithms to aid in their automation, accuracy and robustness.

The overall aim of the knee segmentation system is the fully automated, robust and accurate segmentation of the cartilages. To achieve this goal, the knee system consists of several segmentation stages, with simpler structures segmented first and used to aid in the segmentation of more difficult regions afterwards. The primary purpose of the bone segmentations is to aid in the initialisation of the cartilage models; this is achieved by utilising the strong spatial relationship between the bones and the cartilages.

2.1. Methodology

This work used a knee database provided by Brigham and Women’s Hospital that consisted of 12 normal adults scanned using 1.5 and 3 T G.E. MR scanners with a fat suppressed 3D SPGR MR sequence. The sequence parameters were $t_e = 5$ or 7 msec, $t_r = 60$ msec and a flip angle of $40^\circ$. The FOV was $120 \times 120$ and the acquisition matrix was either $512 \times 512$ or $256 \times 256$. These were reconstructed to images with dimension of $0.23 \times 0.23$ or $0.46 \times 0.46$ and slice thickness of 1.5mm. The bones and cartilages in these images were then interactively segmented by experts.

2.2. Statistical Shape Models

SSMs provide a compact representation of the shape variability from a training set [2]. A SSM is built from a set of $N$ training shapes $s_i$ ($i = 1, \ldots, N$). Each shape $s_i$ has $M$ points sampled on its surface. For this work the shapes were aligned using generalised Procrustes alignment before Principal Component Analysis (PCA) was used to allow the shapes to be written as

$$s_i = \tilde{s} + Pb_i = \tilde{s} + \sum_k p^k b^k_i$$

where $\tilde{s}$ is the mean shape and $P = p^k$ contains the $k$ eigenvectors of the covariance matrix. The corresponding eigenvalues ($\lambda^k$) describe the amount of variation expressed by
each eigenvector. The shape parameters $b = b^k$ are used to control the modes of variation.

To obtain a valid SSM, it is necessary that the coordinates are in a common frame of reference and all the points on each surface correspond in an anatomically meaningful way. For this paper an automated scheme was used to generate the 3D SSMs based on the Point Distribution Model optimisation framework of Davies et al [3].

### 2.3. Optimised 3D Statistical Shape Models

Surfaces and parameterizations of the patella bone and cartilage are obtained using a subdivision based parameterized surface extraction algorithm, which guarantees genus 0 topology. The prototype used for the subdivision was an octahedron for the bone and an icosahedron for the cartilages with the extracted surfaces consisting of 4098 and 10242 vertices. These surfaces are rigidly ICP aligned, centroid matching and RMS normalised. The aligned surfaces are then used to realign the parameterizations.

The correspondence problem is treated by finding the optimal re-parameterization of the surfaces. In this work we used an eigenspace objective function $F = \sum_i \log(\lambda_i + \epsilon)$ with $\epsilon = 0.01$ which was optimised using the Nelder Mead simplex algorithm.

The re-parameterizations are obtained by perturbing the sampling of parameter space and inverse mapping these points onto the corresponding surface (See Figure 3). This is performed using barycentric coordinates that are obtained through an efficient intersection algorithm [13] used in a partitioned parameter space.

The surfaces obtained after the optimisation process are illustrated in Figure 4 and 6 with the correspondence obtained indicated by the colourmap. The statistical shape models created using these surfaces are illustrated in Figures 5 and 7.
2.4. Associating and Embedding Information in Statistical Shape Models

The corresponding points obtained in the optimisation process provide a frame of reference that can be used to extract information of interest from the training datasets. This information can be associated and modeled or embedded into the statistical shape model. This a priori information can then be utilised in segmentation algorithms or our segmentation system to aid in the automation, robustness and accuracy of the results.

We have previously proposed utilising the strong spatial relationship information between the cartilages and the bones of the knee to aid in the automatic initialisation of the cartilage models [5]. The spatial relationship information was embedded or associated in the form of the expected thickness, standard deviation and probability that cartilage exists above the underlying bone into the models of the bone (see Figure 8).

The information that was associated with each point in the statistical shape model and utilised to provide a good initialisation of the cartilage model were

- Probability that cartilage exists.
- Expected Thickness.
- Variance of the Thickness.

In this paper we utilise this information to automatically provide a good initialisation of the patella cartilage model.

3. Automatic Initialisation of Patella Cartilage

Assuming we have already segmented the bones using the statistical shape models, the approach that is currently used to initialise the cartilage model is relatively simple, consisting of rigid body placement of the mean model based on the expected probability and expected thickness. The steps involved in the initialisation of the patella model are as follows,

- The mean shape is placed at the centroid of the points in the probability map with value more than 0.5.
- The scale of the mean shape is set to be the same as the bone model.
- The orientation of the model is extracted from a rigid iterative closest point fit of the model to the points in the probability map with value more than 0.5.
- The model is then translated by half the expected thickness in the direction of defined from the centroid of the bone to centroid of the mean shape.

This could be further extended by allowing the model to deform to obtain the optimal shape parameters using the expected thickness and variance as constraints defined from the underlying bone.

4. Results and Discussion

The placement obtained using the rigid placement of the mean shape of the cartilage model should be sufficient for use in our segmentation algorithms, specifically 3D active shape models. An example of a good initialisation is seen in Figure 9 while a less accurate initialisation is seen in Figure 10.

The approach was validated using voxel based measures to compare the overlap between the automatically placed cartilage model with the real placement of the cartilage for that patient. This was performed by creating a voxel representation of the placed cartilage surface model, that had the same spacing and size as the manually segmented images. Then morphological and connected components filters were used to obtain a closed voxel volume (See Figure 11). These two volumes were then directly compared using standard voxel based measures.

This validation approach is rather inaccurate and leads to a general volume increase, providing only a coarse representation of the original surface in the original voxel space.
However, it is sufficient to illustrate the quality of the initialisation obtained (See Table 1). The results were not performed in a leave one out fashion; however considering that the approach uses a thresholded probability map it would not be expected to change the results significantly. The primary limitation of this approach is that the bone segmentation needs to be obtained using, or matched with, the statistical shape model of the bone.

Table 1. Voxel based measure of the quality of the model placement

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<th></th>
<th>Sensitivity Av (std)</th>
<th>Specificity</th>
<th>DICE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.71150 (0.24921)</td>
<td>0.99238 (0.0047587)</td>
<td>0.44372 (0.19750)</td>
</tr>
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To improve the robustness and accuracy of the initial segmentations the initialisation of the cartilage model could be improved by allowing the estimation of shape parameters. This could be implemented as an iterative optimisation using a function to evaluate the fit of the model to the underlying bone and its expected thickness and variance. However, for each image the initialisation algorithm doesn’t incorporate any image information, so it does not really know where the cartilage is above the bone so it is unlikely to significantly improve the results obtained. The addition of edge or grey level information could be incorporated and turn this into a coarse segmentation algorithm. However, it is not expected that the segmentation algorithms we will be using on the cartilages will require the added accuracy.

5. Conclusion

The strong spatial relationship of the cartilage to the underlying bone has been successfully used to provide a good initialisation of the 3D statistical shape model of the patella cartilage. The accuracy and robustness of this approach was good, although it has only been used on a small database.
This type of approach will be used as an initialisation for the segmentation algorithms used on all the cartilages in the knee. The only proviso with this type of approach is that the segmentation obtained for the bones needs to be made using, or matched with, the statistical shape model of the bone.

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References


