

Automatic Generation of 3D Statistical Shape Models of the Knee Bones

Jurgen Fripp
CSIRO
BioMedIA Lab
jurgen.fripp@csiro.au

Sebastien Ourselin
CSIRO
BioMedIA Lab
sebastien.ourselin@csiro.au

Simon Warfield
Harvard Medical School
Boston
warfield@bwh.harvard.edu

Andrea Mewes
Harvard Medical School
Boston
mewes@bwh.harvard.edu

Stuart Crozier
University of Queensland
ITEE
stuart@itee.uq.edu.au

Abstract

We are working on generating an accurate Statistical Map of the Knee bones and Cartilages for use as ‘a-priori’ knowledge in segmentation algorithms. The approach we are presenting to automatically generate 3D Statistical Shape Models is based on the Point Distribution Model optimisation framework of Davies et al [8]. Our scheme uses a conformal parameterization with an Eigenspace objective function which is then optimized using a Genetic Algorithm. The current technique is illustrated by generating an Optimized 3D Statistical Shape Model of the Patella bone and Non-Optimized Model of the Tibia bone in the knee.

1. Introduction

The impact to the community of health problems associated with the knee is increasing relatively to most other conditions, so that by 2016 it is expected rise from the 10th to the 8th largest major disease and injury Group [1]. Osteoarthritis (OA) is the major contributor to this with 14.6 per cent of Australians suffering from this condition [2]. OA develops when the articular cartilage starts to break down from trauma, aging or failure of joint repair and maintenance mechanisms [11]. It has even been speculated that some forms of OA are the result of a particular type of skeletal remodeling in response to mechanical stress [14]. The degeneration leads to the articular cartilage becoming thin; rough and eventually wearing away, so that bone rubs against bone, thus causing inflammation and chronic pain. As is often the case in medicine the early detection and treatment of OA can significantly improve patient outcomes.

In recent years there has been significant interest in the

use of Magnetic Resonance (MR) imaging to obtain high contrast images of the cartilage, which has lead to several imaging sequences that are useful for imaging the knee [4]. The potential of MR images as a non-invasive diagnostic tool for OA has been demonstrated for severe OA [6]. There are currently two approaches to monitoring OA progression, cartilage volume and cartilage thickness. The use of Cartilage Volume has been shown to correlate with radiographic OA grades and may be more tolerant to knee positioning than thickness measurements [19]. However it is suspected that OA causes regional changes in cartilage structure with some regions thinning and others thickening. For this reason localized measures of cartilage thickness may provide a better picture of OA progression [18].

In healthy patients the articular cartilage is on average 2 mm thick with changes over short time scales (6 - 12 months) usually in the sub-millimeter region [18]. Due to this accurately detecting changes is difficult considering the resolution and accuracy of MRI and segmentation algorithms. That being said it has been demonstrated that both registration [17] of the cartilages and the generation of ‘correspondence’ points by modeling the underlying bone [18] can be used to detect small changes in thickness.

The use of shape analysis techniques on the knee may provide more illumination on the cause and progression of OA by illustrating the specific influence of the biomechanics. The primary problem with this approach is that OA is a degenerative disease, thus the automatic generation of correct correspondence for the cartilages may become difficult. The use of the femur, tibia and patella bones as a referential could help in generating correct correspondence in the cartilages.

The focus of this work is on creating an automated segmentation system for the major components of the knee (bones and cartilages). The primary purpose of the system

is the ‘accurate’ and ‘robust’ segmentation of the cartilages of the knee from MR images. The segmentations can then be used to aid in the detection, diagnosis and treatment of OA. Towards this end we are working on a statistical map of the knee based around 3D Statistical Shape Models. These are currently generated from a database of normal patients obtained from 3D SPGR MR scans. The purpose of this statistical map is to provide statistical constraints on the segmentation algorithms, as well as to provide a basis for analysis of the knee. This paper presents the current methodology used to generate 3D Statistical Models of two of the bones in the knee (Tibia and Patella).

2. Subjects and Imaging

This work is based around a Knee Database provided by Boston Hospital and consists of 24 normal adults who were scanned using 1.5 and 3 T G.E. MR scanners with a fat suppressed 3D SPGR MR sequence. The sequence parameters were TE = 5 or 7 msec, TR = 60 msec and a flip angle of 40°. The FOV was 120×120 and the acquisition matrix was 512×512 and 256×256. These were reconstructed to images with dimension of 0.23x0.23 or 0.46x0.46 and slice thickness of 1.5mm. These images were then interactively segmented by experts.

3. 3D SSM

The Statistical Shape Model (SSM) proposed by Cootes [7] can be used to capture and represent the variation in shape of a set of training examples. So from a set of training data the typical shape and its most significant modes of variation are determined. This shape information can then be used for the segmentation of new image data, restricting the result to legal shape instances of the object to be segmented. This adds an inherent robustness that is necessary for automated segmentation algorithms. Of course to avoid problems in the resulting segmentation process the set of deformations allowed by the model should reflect what is trying to be segmented. This is primarily determined by ensuring there is a sufficiently large training set to cover the ‘real’ variability seen in the object and the accuracy of the ‘correspondence’ on the land marking.

The primary problem in generating 3D SSMs is obtaining correct ‘correspondence’ of the landmarks across the training set. There are several different approaches that have been previously used. The most popular approaches are based around ATLASes [15], Parameterizations, Medial Representations, and recently optimisation approaches.

ATLAS based approaches involves the creation of an ATLAS with a corresponding mesh which is then fitted to the other datasets. There have been two main approaches to fitting the ATLAS to training datasets, registration [15] [10]

or deformable models [13]. The major drawback to this approach is that the the correctness of the correspondence is purely determined by the ‘registration’ or ‘deformable’ model algorithm used.

The parameterized approach solves the ‘correspondence’ problem by mapping the surface of the objects to a spherical surface. The correspondence is obtained by aligning the parameter space [5]. The major drawback of this approach is that generally they are restricted to ‘genus 0’ objects and the correctness of the correspondence is purely determined by the mapping and alignment of the parameterization.

The explicit creation of 3D Medial Representation of the object of interest would be an elegant way of solving the problem [16] [20]. However only certain anatomical shapes are suited to Medial Representation as it is usually difficult to generate a consistent skeleton representation across all the training sets. This is a major problem and makes it difficult to create a good representation which has ‘correct’ correspondence across the training dataset.

Davies etal [8] [9] work is similar to the parameterization work, however it treats the ‘correspondence’ of the landmarks as an optimisation problem. So for a training set of surfaces the aim is to find the optimal placement of the landmarks that minimizes the description length of the whole set. This approach has been shown to perform better than approaches like SPHARM [16] and there is no theoretical reason to suspect that Medial Representations or Registration approaches should outperform it. The primary problem with the current approach of Davies is that it is restrictive to ‘genus 0’ surfaces. However, for the components of interest in the knee they are or can be treated as genus 0 objects.

The primary interest is in using a generic semi-automated SSM implementation that could be applied across a wide variety of objects in the knee, some of which can have a high variability. This is especially true for the cartilages of the knee. Medial Representations are not really suitable for the objects of interest and although ATLAS based approaches are applicable we instead chose to use an approach similar to Davies Point Distribution Model optimisation framework. This was implemented slightly differently using a conformal parameterization with an Eigenspace objective function that is optimized using a Genetic Algorithm. The approach and reasoning behind these choices will be examined in the following sections.

4. Statistical Shape Modelling of the Knee

The SSM framework of Cootes [7] extends trivially to 3D. The SSM is built from a set of N training shapes s_i ($i = 1, \dots, N$). Each shape s_i has M points sampled on its surface ($s_i \in \mathbb{R}^{3M}$). Then using Principal Component

Analysis (PCA) each shape can be written as

$$s_i = \bar{s} + P b_i = \bar{s} + \sum_k P^k b_i^k \quad (1)$$

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

However to obtain a valid SSM it is necessary that

- The coordinates are in a common frame of reference.
- All points on each surface must correspond in an anatomically meaningful way.

The first requirement can be achieved in a preprocessing stage. The second is ensured by using an implementation of the Point Distribution Model optimisation framework of Davies et al [8].

The implementation of the Point Distribution Model optimisation framework that is used can be broken down into 3 stages.

- Pre-processing: Surface Extraction and Parameterization.
- Generation of Initial SSM: created using uniform land marking of parameter space.
- Optimize SSM: Using a genetic algorithm we optimize the objective function of SSMs that are generated from perturbing the uniform land marking via parameters defined in the genome.

4.1. Pre-processing: Surface Extraction and Parameterization

The Femoral and Tibia bone are truncated in MRI scans of the knee. So to treat these as equivalent shapes, the shaft length is truncated so that it is proportional to the width of the head. The surfaces of all the bones (Tibia, Femur and Patella) are then extracted using Marching Cubes. As the MR images are anisotropic a linear transform is used on the surfaces to generate an isotropic surface which reduces the effect of differences in knee alignment. Ideally a better surface interpolation algorithm should be used to generate a more anatomically correct surface. The surfaces are then centroid matched and rescaled so that Root Mean Square distance of the vertices is 100. The rescaling minimizes the influences of the size of the shape biasing the optimisation process.

A Parameterization of a surface is simply a mapping from the surface to a suitable domain. For this work the mapping is from a 'genus 0' surfaces to a unit sphere which provides us with a



Figure 1. Overview of Stage 1

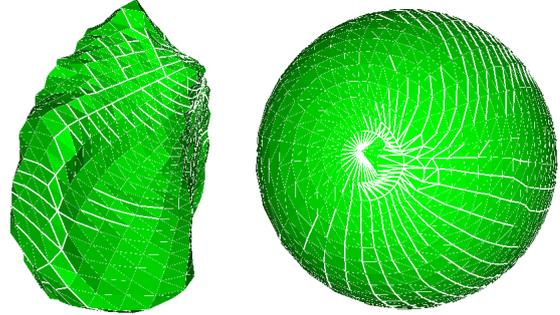


Figure 2. A Patella Surface and its Parameterization

- Canonical space to compare and manipulate the training objects.
- Bijective mapping.

The parameterization method used in this work is a conformal parameterization algorithm of Haker [3]. It does introduce some angular distortion towards the poles, however it is stable and converges relatively quickly for even the extremely large meshes generated by the marching cubes algorithm (for high resolution scans of the femur upwards of 500K vertices). A second pass optimisation scheme can be used to improve the properties of the parameterization (especially area preservation). However for the parameterization of the bones it was not found to be essential. The primary advantage of ensuring a reasonable level of area preservation is that it implies that 'uniform' sampling of the parameter space corresponds to uniform sampling of the surface.

4.2. Initial SSM Generation

Given a training surface and its parameterization a re-meshed surface can be created by re-sampling (land marking) parameter space and then inverse mapping the vertices (land marks) onto the training surface (see Figure 4). For this work a quasi uniform sampling of the sphere was generated using a level 5 or 6 decomposition of an octahedron (1026 or 4098 vertices) whose vertices are then projected onto the unit sphere. Each vertex can be inverse mapped back onto the surface using barycentric coordinates. A Spatial Hashing algorithm is used to make the inverse map-

ping efficient and almost independent of the size of the surface [12].



Figure 3. Overview of Stage 2

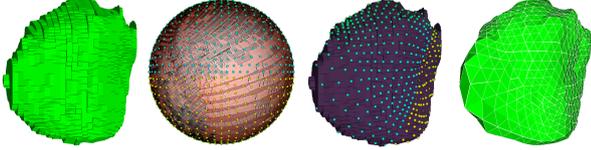


Figure 4. Patella: *left to right* Marching Cubes Surface, uniform sampling of Parameter Space, and Re-meshed Surface (level 5, 1026 vertices)

This procedure is used on each surface in the training set. This set of shapes is then used to generate an initial SSM as outline in section 4. At this stage there is no expectation that the shapes have correct correspondences.



Figure 5. Case 20: *left to right* Land Marks from inverse mapping quasi uniform sampling of parameter space. Visualized over Marching Cubes Surface (level 6, 4098 vertices)

4.3. optimisation of SSM

The initial quasi uniform sampling is optimized using a genetic algorithm. This is done by perturbing the vertices in parameter space for each shape and then evaluating the SSM generated. The perturbation is performed using Cauchy kernels that are placed on the unit sphere. A symmetric theta transform is then used to perturb the vertices (see equation 2).

$$f(\theta, \alpha, A) = \frac{1}{1+A} \left[\theta + A \cos \left(\frac{(1+\alpha^2) \cos(\theta) - 2\alpha}{1+\alpha^2 - 2\alpha \cos(\theta)} \right) \right] \quad (2)$$

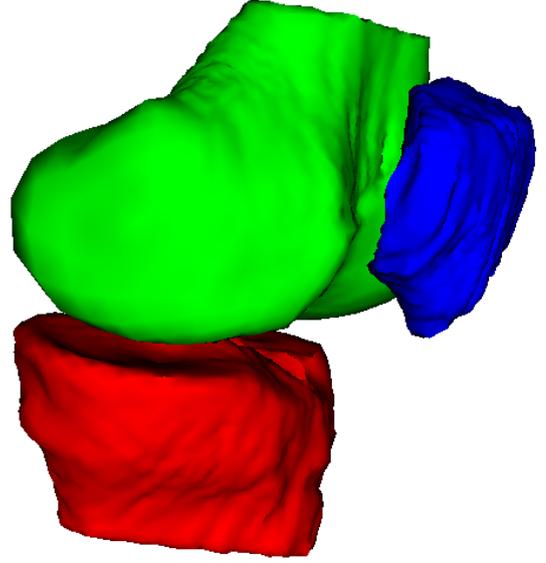


Figure 6. Case 20: The surfaces generated from the quasi uniform sampling of parameter space (level 6, 4098 vertices)

where $\alpha = e^{-a}$, $a \in \mathfrak{R}$ is the width of the Cauchy kernel and A is the amplitude. A genetic algorithm is used to optimize the amplitude of the kernel while the width of the kernel is kept fixed. This allows the implementation of a hierarchical optimisation scheme, which for each level applies finer (localized) perturbations to improve the correspondence of the land marking. This is achieved by generating more densely spaced kernels at each level of optimisation with a reduced width that is fixed based on the level. The kernels are placed on the sphere using an octahedron decomposition with each level of the decomposition corresponding to a level in the optimisation. The width is fixed per level to $a = 2^{level-2}$. The perturbed land marks are then used to generate a new model, which is evaluated using an objective function F ; in this case we used $F = \sum \log(\lambda + \epsilon)$ where λ is the eigenvalue of the mode.

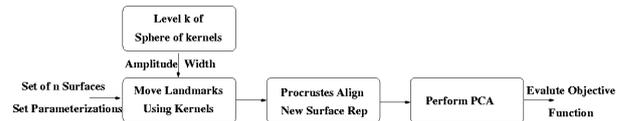


Figure 7. Overview of Stage 3

5. Results and Discussion

Initial models for the two bones (Tibia and Patella) were generated using 8 training sets that were chosen based on the similarity in the ‘size’ of the femur and tibia shafts in the MRI. These models were generated using a quasi uniform land marking of 4098 vertices. Although the parameter spaces are aligned, there is no true correspondence. The result of this problem is especially evident in the tibia (see Figure 8). The eigenvalues of the initial statistical shape model can be seen in Table 5 and the primary mode is shown in Figure 8.

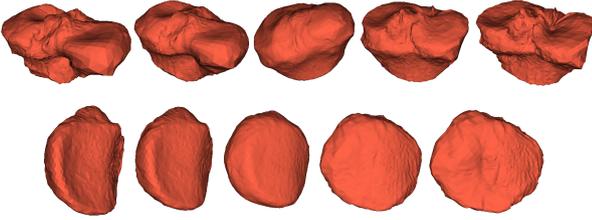


Figure 8. Mode 0: $-\sqrt{3}\sigma, -\sigma, mean, \sigma, \sqrt{3}\sigma$

Mode	Patella (Initial)	Tibia (Initial)
1	468858	540341
2	138412	188464
3	86952	137906
4	55534	76362
5	47659	52988
6	33933	37121

Table 1. Eigen-values of primary modes of variation for initial model of Patella and Tibia

The primary limitation of our optimisation scheme is the high computational cost of the genetic algorithm based optimisation scheme. The main computational cost in this scheme is the inverse mapping. The use of a spatial hashing algorithm has improved the speed of the inversion by at least an order of magnitude and it is also less dependent on the size of the surface mesh. The current limitation is simply the memory required to store and process sets of very large meshes. Although reading the meshes into and out of memory is a possible approach, the preferred solution is to perform quality re-meshing on the dense surfaces to reduce the mesh size while preserving shape information. A quality re-meshing algorithm is still under development.

In the knee database, the dense surfaces that are generated have between 25k to 500k vertices. The Patella have between 25k to 70k vertices, the tibia has 60K to 250K and

femur 150K to 500K. So although the parameterizations and an initial model can be generated for use in the optimisation scheme the Patella was the only bone optimized.

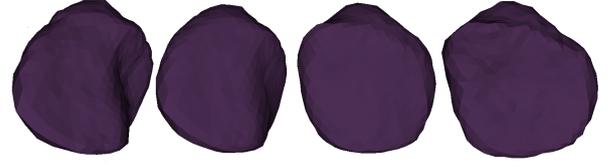


Figure 9. Mode 0: $-\sqrt{3}\sigma, -\sigma, \sigma, \sqrt{3}\sigma$

The Patella was trained using 12 arbitrary training sets from the database and a quasi uniform land marking consisting of 1026 vertices was used. For the Patella the optimisation scheme improved the local correspondence of the land marks compared to the initial model. The optimisation process improved the compactness of the models compared to uniform land marking of parameter space by about 10 per cent.

Mode	Patella (Initial)	Patella (Optimized)
1	83862.9	81986.6
2	26238.2	25595
3	19816.6	15443.3
4	17836.8	11452.7
5	11281.3	11092.2
6	9759.72	9592.65

Table 2. Eigen-values of primary modes of variation for the Patella

6. Conclusion

The statistical shape models generated using this optimisation scheme are a reasonable basis for segmentation algorithms. Currently it is necessary to optimize the initial model, as the correspondence from parameter space is not sufficient. The current optimisation scheme is only computationally efficient for surface meshes with around 100K vertices. A quality re-meshing algorithm is under development to reduce the large dense surfaces to a more computationally feasible size which can also be accommodated in memory. This will be essential when a more complete generation of the shape statistics of the knee is performed, as this will require the training of many more datasets. It is expected that 50 or more training datasets need to be used to adequately encompass the variability in 3D model generation.

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