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Statistical modelling of the whole human femur incorporating geometric and material properties

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ABSTRACT

When analysing the performance of orthopaedic implants the vast majority of computational studies use either a single or limited number of bone models. The results are then extrapolated to the population as a whole, overlooking the inherent and large interpatient variability in bone quality and geometry. This paper describes the creation of a three dimensional, statistical, finite element analysis (FEA) ready model of the femur using principal component analysis. To achieve this a registration scheme based on elastic surface matching and a mesh morphing algorithm has been developed. This method is fully automated enabling registration and generation of high resolution models. The variation in both geometry and material properties was extracted from 46 computer tomography scans and captured by the statistical model. Analysis of mesh quality showed this was maintained throughout the model generation and sampling process. Reconstruction of the training femurs showed 35 eigenmodes were required for accurate reproduction. A set of unique, anatomically realistic femur models were generated using the statistical model, with a variation comparable to that seen in the population. This study illustrates a methodology with the potential to generate femur models incorporating material properties for large scale multi-femur finite element studies.

1. Introduction

Orthopaedic implant designs undergo extensive preclinical testing to ensure their reliability, but once in use their performance can vary dramatically between patients. There are two significant areas of variability not commonly considered in conventional computational studies, which could account for these differing outcomes. These are surgical skill [27] and the bone structure and quality of the individual patient [24,47]. The vast majority of traditional studies use a single or limited number of bone models and vary parameters related to implant design. This sacrifices quantitative accuracy by ignoring natural interpatient variability [30]. Without the inclusion of such parameters, it is difficult to extrapolate the results of these studies to assess the suitability of an implant for the population as a whole. Without robust and reliable automated model generation techniques the time consuming and laborious task of creating multiple models from sources such as computer tomography (CT) scans is a significant limitation preventing multi-subject-based finite element (FE) studies becoming commonplace. Along with this, the often limited availability of such source data is also inhibitive [44,32]. This work investigates the potential of developing a statistical model to use as a source of FE bone models as a possible solution to the problem of model generation and limited data availability.

Statistical deformation models have been widely used and developed in computer vision to capture the variations possible within a class of shapes. PCA is often the method of choice for statistical deformation model construction, requiring point to point correspondence to be established between each example shape usually by manual or semi-automatic placement of landmark points along boundaries (Active Shape Models) [12], or image intensity matching (Active Appearance Models) [11]. Alternative approaches to achieve correspondence have been developed but are more computationally expensive to implement [14,8]. The resulting statistical model can then be used to identify the shape in a new image or to generate a unique instance of the shape. However, because of the field in which these and other similar techniques have been developed they are often only suited to two-dimensional images. Extending them to three-dimensional shapes leads to a dramatic increase in complexity and creates a challenge in establishing

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accurate correspondence between any landmarked points. Registration of each of the training images must therefore be carried out in order for the model to be built. For many applications rigid registration techniques have proved sufficient, such as the Iterative Closest Point (ICP) algorithm [3], used by [46] to create a statistical model of bones in the hand, which has the advantage of not requiring a predefined relationship between points on the objects being registered. This is not true for more complex biological applications such as comparing breast MRI scans [35], brain images [36,1] and bone anatomy [2] where the shapes are highly deformable. In these cases non-rigid registration techniques have been required based on computationally demanding free-form deformation (FFD) models, although alternative techniques have been employed by [48,14,9,33] and [42]. A mesh matching approach was developed by [13] to automatically generate three-dimensional, patient specific, finite element meshes of the proximal femur.

Although several of the techniques discussed use intensity-based approaches to match models but few have carried these material properties through to the final model, instead focusing on shape changes. An exception is [31], where non-rigid registration in the image-space was employed in conjunction with principal component analysis to construct a statistical shape and intensity model of the proximal femur based on only 11 subjects. In theory image-space registration schemes which make use of intensity-based similarity metrics can lead to a more realistic statistical shape and intensity model. However, this approach is computationally expensive for high resolution images (such as good quality CT scans) and the statistical model output is not FE ready, each instance would require meshing after generation.

This paper proposes a registration technique based on an extended elastic matching scheme [28] and a mesh morphing algorithm [34,21,41] to allow the construction of a statistical femur model using principal component analysis (PCA), and analyses its ability to achieve the criteria for which it was developed. The ultimate aim being that the statistical model would generate femurs as solid tetrahedral meshes with associated material properties, that could be used directly in FE analysis. The technical implications of this are that the algorithms must handle the complexity required for the mesh density associated with FE studies [29], with an efficiency that makes the process feasible and mesh quality retained so remeshing is not required. The registration scheme must be able to accurately capture the complex, variable shape and material distribution of the femur, without which any generated models could produce an unrealistic population of femurs and so be of no use to later studies.

2. Methods

In order to achieve the objectives of this paper, a statistical model of the whole femur was trained using a data set of femur models extracted from real subject CT scans. The significant challenge in doing this is establishing correspondence between each training example in such a way that the location and material properties at any given point in one model can be directly related to an equivalent point in another model. The approach taken in this work was to morph a common baseline tetrahedral mesh onto each training example. An overview of the steps taken is as follows:

1. Segment out the region of interest, i.e. the femur, from each CT data file and describe its shape as a dense cloud of surface points.
2. Select one femur instance as the baseline or reference to which each other model will be matched and convert this model into a high quality solid tetrahedral mesh.
3. Register the baseline femur to each training example using a two stage process of (1) surface registration, based on an elastic matching algorithm and (2) a volume mesh deformation strategy.
4. Assign every point in the morphed meshes a greylevel value from their original CT scan files using a material property extraction program.
5. Construct a Point Distribution Model using the mesh-based femur representation complete with material properties and create the statistical model using principal component analysis. The statistical model produces a volume mesh along with spatially varying material properties that can be directly used by a finite element solver.

2.1. Data preparation

Semi automated segmentation of bone from surrounding soft tissue was achieved with greylevel thresholding tools and manual slice-by-slice corrections using Avizo (Visualization Sciences Group, USA/France) formerly VSG of Mercury Computer Systems, USA. The extracted geometries were each described as a surface mesh of nodes and connectivities, together forming a training set for the statistical model. In order to eliminate variation between the models due to patient positioning during scanning an Iterative Closest Point (ICP) algorithm [3] was applied to each model to align them to the same approximate orientation with a coincident center of mass. This automated procedure had the advantages of time efficiency and reducing potential alignment, and later registration, errors over manual schemes.

2.2. Baseline mesh

The baseline mesh was created from the median length femur, chosen with the rationale that this would lead to the minimum element distortion when stretching or compressing the mesh to fit another instance. The reference femur was imported into meshing software, ANSYS ICEM CFD^{TM} (ANSYS, Inc., Canonsburg, PA), and converted into a high quality, 4-noded tetrahedral element mesh with a global element size of 3 mm. In order to balance model definition and computation cost the model was then split into three regions and the upper and lower thirds' mesh size refined to 1–1.5 mm at the surface. This was justified for three reasons: (1) these areas are of more clinical interest so a fine mesh will be important for future use of the model, (2) these areas contain the most rapidly changing geometry and hence require a higher density of surface points to achieve accurate registration and (3) Perillo-Marcone et al. [29] recommended choosing a element size equivalent to the CT slice distance in order to achieve convergence of material property distribution. The baseline tetrahedral mesh, and therefore any subsequent mesh produced by the model, consisted of 615,523 elements and 117,225 nodes, of which 27,171 were on the surface.

2.3. Registration strategy—surface registration and volume morphing

The aim of the registration scheme was to manipulate the baseline tetrahedral mesh to achieve three-dimensional correspondence to the geometry of each of the other femurs, where each target femur is represented as a surface mesh. The developed process had two stages: (1) surface registration based and (2) volumetric morphing.

A surface registration scheme was originally developed based on an algorithm proposed by Moshfeghi et al. [28]. Two key modifications were made to allow registration of the high density meshes in this study. Firstly k-d trees [38] were used for nearest neighbour searching, this is a computationally efficient method of accelerating nearest neighbour searching in a large data set. Secondly Laplacian