MR Bone Atlases for Shape Characterization

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Introduction:
Dual Energy X-Ray Absorptiometry (DEXA) is currently the most commonly used quantitative radiological method to assess bone mineral density (BMD) in adults. However, there is an increasing awareness that BMD is not the sole indicator in determining risk of fracture but that other values including bone shape (morphology) and quality also play an important role [2]. In this paper, we report a strategy based on free-form transformation to generate an average shape atlas of the femur and tibia and apply it to study bone shape differences in a population cohort. This strategy has potential application in detection of subtle shape differences in normal and diseased population groups.

Material and Method:
MR images of 10 male subjects, age range of 22-29 years and free from any chronic or acute knee conditions were acquired at 3.0 T (Magnetom Trio®, Siemens) with a phased array knee coil, using a 3D Steady State Free Precision (SSFP) sequence with sagittal slices. The imaging parameters were: TR/TE: 8.65/4.33, matrix: 512×512, FOV: 160×160, slice thickness: 1.5 mm with whole volume coverage. The raw MR data was interpolated to pixel resolution of 0.3×0.3×0.3 mm^3 prior to registration. The femoral and tibial bones were manually segmented from the images to create atlases of the same in the following steps:

$$v_{n+1} = G_\sigma \otimes \left(v_n + G_\sigma \otimes \frac{1}{2}\left[\frac{C(T-S)\|\nabla S\|\|\nabla T\|}{\left(\|\nabla T\|^2+\|\nabla S\|^2\right)\left(\|\nabla S\|^2+\|\nabla T\|^2+2(T-S)^2\right)} \nabla S \right]\right) \quad [1]$$

Step I: One subject with an average age and BMI value of the group was chosen to serve as a reference to which the rest of the images in the group of subjects were aligned utilizing mutual information based affine transformation. This corrects subject positioning and global size differences. *Step II:* An elastic registration based on demons algorithm [3] was employed to locally map all the images in the group of subjects to the reference image using the affine transformation parameters as an initial estimation. This provides 3D deformation fields that can transfer the spatial locations on an individual in the group into the coordinate system of the reference bone. The registration algorithm computes the transformation iteratively using equation 1. ν_{n+1} is the correction vector field at iteration n+1, G_σ is the Gaussian filter with variance σ2, ⊗ denotes the convolution, C is the scaling factor and T and S are the target and transformed images respectively. The algorithm estimates the displacement which maps a voxel at location (x,y,z) in T to the corresponding anatomical location in S. The algorithm is implemented hierarchically and to preserve the morphology, deformation vector fields were computed utilizing both the forward and backward transformation. *Step III*: Mean intensity image with the shape of the reference image is created by averaging the globally and locally transformed images of the group. *Step IV:* Mean deformation field that encodes the shape variation between the reference image and average shape of the elements in the subject group is created by averaging over 3D deformation vector fields of the individual subjects of the group. *Step V:* Average deformation field is applied to the average intensity image to generate an average intensity and deformation image template for the group under study. *Step VI:* Steps 1-5 are iterated till no significant change in the deformation field is observed relative to the previous computation. At the end of each iteration the original reference image is replaced by the average template constructed at *Step V* generating both average shape (morphometric) and intensity atlases that represent the centroid of the population data set.

Active shape and intensity models based on the principal component analysis (PCA) of the deformation fields obtained from the atlas generation were created and used to represent the variance in shape within a given population [4]. The generation of active shape models included the following steps: calculation of mean deformation, computation of deviation from the mean, calculation of the covariance matrix and its eigenvectors and eigenvalues and finally constructing a linear model using the eigenvectors and corresponding weights. The shape variations from the mean shape and intensity along the first two principal modes were generated using the linear model derived from this analysis. These images were synthesized by setting the weights of the first (or second) mode at $\pm 250\sqrt{\lambda}$ and $\pm 500\sqrt{\lambda}$ and all other weights to zero. The synthesized images provide a visual representation of the possible variance in shape and intensity of the femur and tibia based on ten image sets used in the atlas creation.

Result and Discussion:
Fig 1shows the registration process in various stages. The affine transform corrects for positional and global scale changes and the local deformation corrects for physiological changes. The accuracy of the alignment can be visually evaluated by the sharp edges of the atlas in the 2D images (Fig. 1) as well as the visualization of a thin structure such as the physis in the 3D rendering of the atlas volume (Fig. 2). Within the population used for this study, there was very little shape variations once the global size was normalized. Thus we chose large standard deviations (±250, ±500 SD) to depict the variance in the population (Fig. 3). Projections of the ten subjects along the first two eigenmodes are shown in Fig. 4. Small deviations from normal shape can be readily detected in this feature space if they do not follow the linear relationship seen for normal bone shape (Fig. 4).

In conclusion, we have developed a methodology to create an average shape model of the femur and tibia and determined that there are very small shape variations in this well-defined population. 3D shape coefficients from this model could potentially be used to discriminate normal/diseased states.

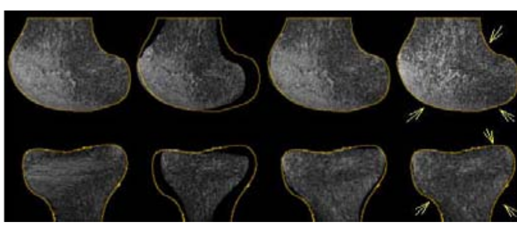

Fig 1. Left to Right: reference, test image, result of affine transform and free form deformation image. Top row (tibia), Bottom row (femur). Outline from reference shown superposed on test & aligned images. Arrows indicate the sharp edges

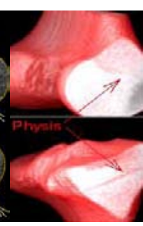

Fig 2. 3D Atlas showing physis

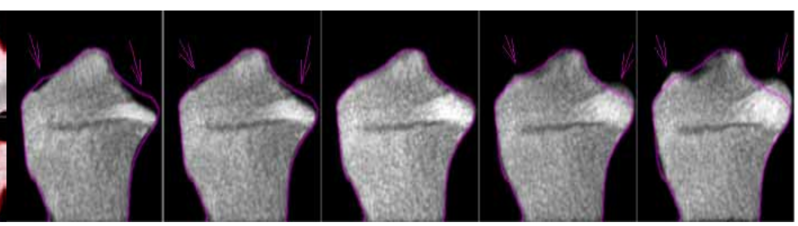

Fig 3. 3D active shape models. Average shape shown in the middle with standard deviation (SD) variations along the first mode shown: Left to Right -500 SD, -250 SD, +250 SD and +500 SD. Arrows indicate regions with changes from average bone shape.

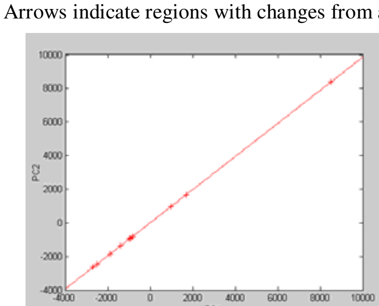

Fig 4. Projection of ten subjects along the first two eigen modes.

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