Efficient Mechanical Bone Parameter Estimation on the Basis of Grayscale Magnetic Resonance Images

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Introduction: In addition to bone volume fraction, trabecular network architecture is known to significantly impact overall bone strength [1]. Whereas μMRI-derived structural trabecular bone (TB) parameters have been shown to predict fracture risk, finite element (FE) analysis on the basis of MR image input is arguably a more direct measure of mechanical bone strength. As with all measurements of TB strength on the basis of non-invasively acquired images, the main challenge is posed by the relatively large voxel dimensions (150 μm or larger) [2,3]. Since thickness of individual trabeculae is on the order of 100 μm, most image voxels are only partially occupied by bone, thus binarization of the data can entail significant errors. A second challenge associated with image-based FE modeling is the long computation time required.

To address these issues, we have developed a custom FE solver that takes as input a 3D grayscale bone-volume fraction maps (derived from a 3D sub-region of a MR image). The program outputs the mechanical parameters in the form of six elastic coefficients (three Young's and three shear moduli). The algorithm largely follows the methods proposed by van Rietbergen et al [4]. Among the advantages of our custom algorithm is the relatively short computation time, which is achieved by estimating an initial solution and choosing the criteria for convergence specific to our particular application.

The software has been used in recent ex-vivo studies to demonstrate the role of structural parameters (over and beyond bone-volume fraction) as a predictor of bone strength [5] and to investigate the relative contributions of trabecular and cortical to overall bone strength [6]. The purpose of the present study is to investigate alternate criteria for convergence of the algorithm, and to demonstrate the importance retraining grayscale information at in-vivo resolution.

Methods: The finite element solver was implemented in pure C++ on a Linux workstation with dual quad core Xeon CPUs (3.16 GHz) and 28 GB of RAM. For efficiency, four to six simulations ran simultaneously on separate CPUs of the same machine. The algorithm largely follows the implementation in [4], with each voxel being modeled as a single hexahedral (brick) element. The displacement function is assumed to be continuous and tri-linear on each element, thus giving three free displacement parameters for each (non-boundary) vertex (Δx_i, Δy_i, Δz_i,), and three boundary conditions for each vertex on the boundary of the volume. By minimizing the total elastic strain energy over the entire structure, a linear system is obtained (relating the displacement at each vertex with the displacements at neighboring vertices), with 3N equations and 3N unknowns, where N is the number of non-boundary vertices. The linear system depends on Young's modulus E_i and Poisson's ratio ν_i at each voxel, with the right-hand side depending on the applied boundary conditions, which are set to simulate various forms of loading. This (sparse) linear system was solved for each simulation using a preconditioned conjugate-gradient algorithm.

The algorithm was applied to images in a number of studies, including in-vivo μMRI, ex-vivo μMRI, and ex-vivo μCT. Fig. 1 shows the processing steps for one of 30 distal tibia specimens from 15 donors (ages 55-85 years) obtained with a 3D spin-echo sequence [7] after marrow substitution with gadolinium-doped water at 1.5T field strength (128 slices at 160x160x160 μm^3). The data were first normalized and inverted so that intensities represented the fractional voxel occupancy by bone (BVF). These were then used as input to the mechanical modeling software, with Young's modulus for each voxel proportional to BVF, with 100% = 15 GPa.

These specimens were also scanned using μCT at 25 μm isotropic (μCT 80, Scanco Medical, Switzerland). To demonstrate the importance of retaining the grayscale information, μCT data were processed at two downsampled resolutions: 50 μm isotropic and 175 μm isotropic. At the lower resolution, two versions were analyzed, grayscale and binarized using simple thresholding.

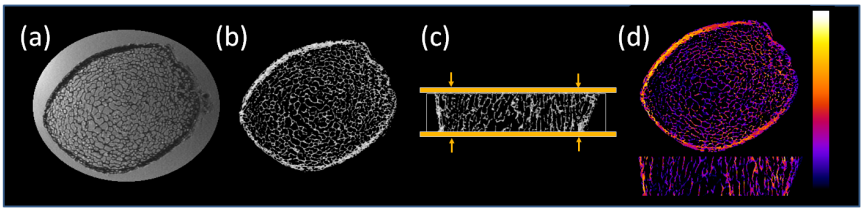

Fig. 1. Steps in a whole-bone micro-FE analysis. (a) Original grayscale acquisition; (b) normalized and inverted BVF map; (c) simulated compression test; (d) resulting strain map (axial and longitudinal views).

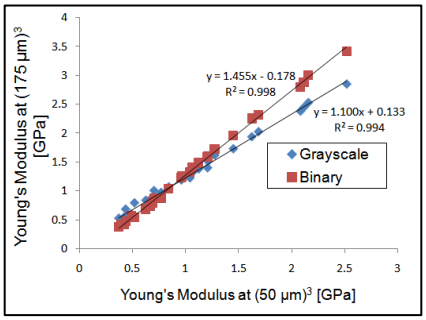

Fig. 2. Young's modulus for compressive loading along the bone's main loading direction computed from downsampled data versus that computed at high-resolution for both grayscale and binarized images.

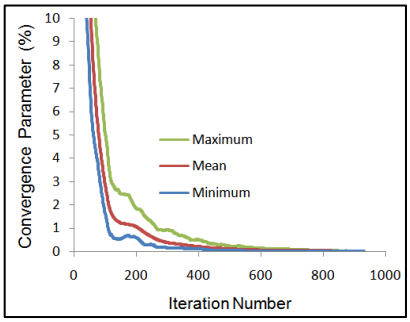

Fig. 3. Minimum, maximum, and mean convergence parameter as a function of iteration number for 28 *in-vivo* image datasets from the distal tibial metaphysis.

Results and Conclusions: For the whole-bone analyses (around 2 million elements per simulation), each simulation completed in around one hour (effectively 15 minutes/simulation as four processes ran simultaneously). Fig. 2 compares computed moduli obtained at in vivo and μCT resolution. While both grayscale and binary datasets correlate well with high-resolution, the grayscale images match better in terms of slope being closer to unity (1.10 vs. 1.45), suggesting that retaining grayscale information is indeed important at the lower resolution.

The rate of convergence is shown in Fig. 3 for the in-vivo MR datasets. Here the 'convergence parameter' represents the percent deviation from the ending surface forces throughout the conjugate-gradient iterations. We have observed that this parameter tends to converge faster than the (more classically used) residual in the conjugate-gradient algorithm, and is more directly related to the physical parameter being computed. For example, a convergence parameter of 1% roughly corresponds to a 1% error in the computed Young's modulus. The results suggest the method to be practical for mechanical assessment of trabecular bone mechanical competence on the basis of in-vivo high-resolution MR images as input into a FE model.

References: [1] Legrand et al, J Bone Miner Res 15:13-19 (2000); [2] Wehrli et al, Proc IEEE 91:1520-1542 (2003); [3] Majumdar et al, Top Magn Reson Imaging 13:323-334 (2002); [4] van Rietbergen et al, J Biomech 28:69-81 (1995); [5] Magland et al, Proc ASBMR (2008); [6] Rajapakse et al, Proc ASBMR (2008); [7] Ma et al, Magn Reson Med 35:903-910 (1996);

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