Optimization of Nonlinear Hyperelastic Coefficients for Foot Tissues Using a Magnetic Resonance Imaging Deformation Experiment

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Accurate prediction of plantar shear stress and internal stress in the soft tissue layers of the foot using finite element models would provide valuable insight into the mechanical etiology of neuropathic foot ulcers. Accurate prediction of the internal stress distribution using finite element models requires that realistic descriptions of the material properties of the soft tissues are incorporated into the model. Our investigation focused on the creation of a novel three-dimensional (3D) finite element model of the forefoot with multiple soft tissue layers (skin, fat pad, and muscle) and the development of an inverse finite element procedure that would allow for the optimization of the nonlinear elastic coefficients used to define the material properties of the skin muscle and fat pad tissue layers of the forefoot based on a Ogden hyperelastic constitutive model. Optimization was achieved by comparing deformations predicted by finite element models to those measured during an experiment in which magnetic resonance imaging (MRI) images were acquired while the plantar surface forefoot was compressed. The optimization procedure was performed for both a model incorporating all three soft tissue layers and one in which all soft tissue layers were modeled as a single layer. The results indicated that the inclusion of multiple tissue layers affected the deformation and stresses predicted by the model. Sensitivity analysis performed on the optimized coefficients indicated that small changes in the coefficient values ($\pm 10\%$) can have rather large impacts on the predicted nominal strain (differences up to 14%) in a given tissue layer. [DOI: 10.1115/1.4023695]

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Introduction

Parametric analyses using finite element (FE) models of the foot have been used to make important contributions to the understanding of interactions between the foot and its mechanical environment. For example, FE foot models have been used to investigate the effects of surgical decisions [1,2] and insole geometry, material, and thickness [3,4] on plantar pressure distributions. Another desirable application of FE foot models is the prediction of quantities such as the distributions of plantar shear stress and internal stress for which measurement techniques are either limited [5–7] or currently unavailable. Accurate prediction of these quantities would provide valuable insight into the mechanical etiology of neuropathic foot ulcers, a complication estimated to affect 15% of all people with diabetes at some point during their life [8].

Prediction of internal stress distribution with FE requires that the FE models incorporate realistic geometry, boundary conditions, and material properties. Unfortunately, realistic descriptions of the material properties of the soft tissues of the foot are difficult to obtain because *in vivo* characterization of individual tissue layers, such as skin, fat, and muscle, are difficult and uncommon. To avoid the need for realistic models of each foot tissue component, many FE models of the foot have combined all of the plantar soft tissue layers into a single layer and modeled this structure

using a single set of material properties [1,3,4,9–12]. Although the resulting FE models have correctly described the deformation of the surface of the foot (which is useful for predicting surface pressure), they are unable to distribute internal loads according to the discrete structures of the foot and therefore cannot be used to predict the distribution of the internal stresses.

Recognizing this limitation of the lumped material model, several studies have been published in which discrete soft tissue structures including the skin and plantar fat layers have been incorporated into 2D FE models of the heel pad and forefoot to study internal stress distribution [13–15]. However, these studies have relied on material models generated from *in vitro* testing of human or animal tissues to define the material properties of these structures [16–20]. The use of material properties obtained from *in vitro* testing is limited by questions about the effects of tissue degradation, sample boundary conditions, hydration, and temperature on the resulting material properties. An *in vivo* technique that can provide the same information in a noninvasive, foot-specific manner would provide an attractive alternative to *in vitro* experiments.

In vivo material coefficient optimization requires a test in which data describing tissue deformation is recorded under known loads as well as a method for determining material properties from imaging data. Magnetic resonance imaging (MRI) [21], computed tomography (CT) [22], and ultrasound (US) [23] all have been utilized in the past to record *in vivo* tissue deformation. However, due to its capability to generate images with high soft tissue contrast, MRI is especially well suited to visualize the deformation of individual tissue layers in 3D and has been used in the past to determine linear material properties of foot tissues [24–27].

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Inverse FE analysis can be utilized in conjunction with MRI images of soft tissue deformation to optimize the material property coefficients of the soft tissue layers of the foot *in vivo* if the loading conditions responsible for the imaged deformation are known (e.g., [14,28]). To optimize the material properties of the soft tissue layers of the foot, a detailed FE model including the major tissues of interest (skin, fat, muscles, and bone) must be constructed. Due to practical limitations involving mesh generation and computational power, it is not possible for inverse FE models to include all materials and structures of the foot and the model must be limited to a specific region of interest.

Our investigation is focused on the creation of a novel 3D FE model of the foot with multiple tissue layers and on the development of an inverse FE analysis procedure that would allow for the optimization of the nonlinear elastic coefficients used to define the material properties of the skin, fat, and muscle layers in a model of the forefoot based on a Ogden hyperelastic constitutive model. The coefficients determined from the inverse FE analysis can be evaluated based on the difference between experimental and model predicted deformations.

Methods

Imaging. Following Institutional Review Board approval, axial T1 weighted MRI image sets were acquired of the right forefoot of a healthy male subject (21 years, 1.68 m, 61 kg) with an OrthOne[®] one Tesla extremity MRI scanner (ONI Medical Systems, Wilmington, MA). Image sets were acquired in both unloaded and loaded states using a previously described MRI-compatible foot-loading device that deformed the foot by compressing it between a rigid fiberglass cast at the dorsum and a plastic plate at the plantar surface [21] (Fig. 1). A total of five image sets were acquired, one of the foot in the undeformed condition in which no loads were applied and one set each in which a compressive load equal to 12.5% (75 N), 25% (150 N), 37.5% (225 N), and 50% (300 N) of the subject's total body weight were applied to the forefoot. Figure 2 illustrates the image sets acquired for the undeformed condition and the 12.5% and 50% body weight loaded conditions. Each image set had an acquisition time of 3.5 min and consisted of 54 image slices with an in-plane resolution of 0.274 mm, and an out-of-plane resolution of 2 mm [21].

FE Model Construction. A 3D, multmaterial, FE model of the subject's forefoot was constructed from the unloaded MRI image set. The shapes of the skin, fat pad, metatarsal, and toe bones were manually extracted from each image in the undeformed state using

Fig. 1 The foot-loading device used during collection of MRI deformation data. For a more thorough description, see Petre et al. [21].

Fig. 2 Top: MRI image sets collected in the unloaded state and with 12.5% and 50% of the subject's body weight applied to the forefoot. Middle: The 3D nature of the data allows for visualization and analysis of the tissue deformation along any plane. Bottom: Frontal plane sections through the approximate metatarsal head region. Note that most of the deformation has already occurred when only one quarter of the total load (12.5% BW) was applied.

custom MATLAB[®] (Mathworks, Inc., Natick MA) segmentation software. 3D surfaces were generated as a best fit through the collected points using Rhinoceros3D[®] (McNeel North America, Seattle, WA). All tissues not included in the plantar fat, bone, or skin regions were lumped as muscle, the most prevalent remaining constituent. TrueGrid[®] (XYZ Scientific Applications, Livermore, CA) was used to generate a 3D hexahedral mesh conforming to the objects of interest (Figs. 3(a) and 3(b)). Toes were individually meshed, but did not contain tissue layers as they were included only to carry load during the simulation and to eliminate the need for an assumed boundary condition at the toe-foot interface had the toes been omitted. The resulting mesh contained 26,324 linear, three-dimensional, eight node linear hexahedral elements (Abaqus C3D8H elements) incorporating a hybrid pressure-displacement formulation that accounts for the nearly incompressible nature of soft tissue by constraining the change in the volume of these elements [29].

To reduce the number of degrees of freedom in the model, the phalanges of each toe were fused based on results published by Actis et al. [14] which indicate that fusion of the interphalangeal joints will have little effect on model results. To further simplify the model, the sesamoid bones were assumed to be fused to the head of the first metatarsal. This assumption can be considered a realistic representation of these joints when MTPJ flexion/extension angles are small, as the resulting motion of the sesamoids would be minimal [30]. The metatarsophalangeal joints (MTPJ) were defined through the use of connector elements [29] that allowed for three rotational degrees of freedom while constraining translational motion of the connected structures. The centers of rotation were located at the approximate centers of the metatarsal heads (Fig. 3(c)). The centers of rotation for the tarsometatarsal joints (TMTJ) were located at the approximate centers of the metatarsal bases, with the bases of all metatarsals being attached to a reference node in the midfoot. The midfoot reference node remained fixed in space throughout the simulation to represent a stationary subject in the MRI.

The change in bone pose of the foot in response to loading observed in the MRI data sets results from a combination of surrounding material compression, and passive resistance of ligaments, joint capsules, and other connective tissue. Since these connective structures were not modeled here, the modeled bone pose was prescribed through the use of boundary conditions that constrained the motion of the modeled bones. The boundary conditions were

Fig. 3 (a) The outer surface of the 3D finite element forefoot mesh. (b) The FE mesh with the toes, skin, and muscle removed to display the bones and plantar fat. Note that the phalanges of each toe were fused for this study. (c) Joint definitions used to describe model bone kinematics. Open circles represent the locations of joint centers of rotation. The midfoot node was fixed in space throughout simulation of the loading experiment (see Fig. 1). (d) FE model of the MRI loading experiment incorporating the 3D, layered tissue FE mesh. The midfoot and cast were fixed during the simulation and forces were applied to the rigid plate, as in the MRI experiment.

determined based on the plantar/dorsiflexion and ad/abduction (splay) of each metatarsal and fused phalangeal group observed in the MRI image sets of each loading condition. The motion allowed by these boundary conditions was set based on the change in bone position observed when bones segmented from the unloaded images were overlaid on bones segmented from the MRI images in which the compressive loads were applied.

The mesh representing the forefoot was positioned between a surface representing the rigid cast which was located adjacent to the forefoot dorsally and a surface representing the moving, rigid plate located under the plantar surface of the forefoot to simulate the MRI loading experiment (Fig. 3(d)) [21]. The 114.3 mm (4.5 in.) diameter rigid plate was created from design drawings of the MRI loading device. The cast was created by offsetting the dorsal surface of the foot by 1 mm and applying a smoothing algorithm in Rhino3D to mimic the lightly padded fiberglass cast used in the experiment. The cast toe box was flattened to simulate the stretching of cast material across the top of the loading device. Contact between the foot and the cast was assumed to be frictionless to simulate the effect of an elastic stockinette sleeve, whereas contact between the foot and the plate, where the stockinette was cut away, was assigned a static coefficient of friction of 0.5.

During each simulation, the rigid plate was pressed against the bottom of the foot in four loading increments, equal to those used in the MRI deformation experiments. Motion of the model was restricted by the rigid cast at the dorsum and, through constraints on bone kinematics, by the fixed midfoot. The nodes located on the proximal sectioned surface of the foot were not constrained.

All bones were considered rigid based on the work of Actis et al. [14] who have shown that when the elastic modulus of bones in a foot model is set to a value greater than 7300 MPa, the material properties assigned to the bones have minimal impact on the modeled outcome. The skin, fat, muscle, and lumped toe soft tissue were described as first order Ogden hyperelastic materials to account for the nonlinear, finite strain behavior of these tissues [31]. This model also accounts for compressibility. The Ogden material model defines the strain energy density function W in terms of powers of the principal deviatoric material stretches:

$$W = \frac{\mu}{\alpha^2} (\lambda_1^\alpha + \lambda_2^\alpha + \lambda_3^\alpha - 3) + \frac{1}{D} (J - 1)^2 \quad (1)$$

where $\lambda_i = 1 + \varepsilon_i$, ε_i = the i th principal deviatoric strain of the left Cauchy-Green strain tensor $\mathbf{C}$, and J = the determinant of the deformation gradient $\mathbf{F}$ (equal to the ratio of the deformed and undeformed infinitesimal volumes). The coefficients μ (units of stress), α (unitless), and D (units of 1/stress) describe the nonlinear response of the material. Stresses are obtained by differentiating the strain energy density function with respect to the deformation, i.e., $\sigma = (\partial W / \partial \lambda)$. Although material coefficients are phenomenological in nature, some coefficients do have physical meaning. In the case of the Ogden model, the coefficients μ , α , and D account for the initial material stiffness, the strain hardening behavior of the material, and the material compressibility, respectively. As seen in Eq. (2), the parameter D is a function of both the effective Poisson's ratio ν and the initial shear modulus μ_0 :

$$D = \frac{2\mu_0(1+\nu)}{3(1-2\nu)} \quad (2)$$

Optimization of Material Coefficients. An inverse finite element optimization technique was used to determine the most appropriate material coefficients to describe the subject's forefoot skin, fat, and muscle (Fig. 4). This process required that both Ogden material coefficients be optimized for each tissue requiring a total of six coefficients be optimized ($\mu_{\text{skin}}, \alpha_{\text{skin}}, \mu_{\text{fatpad}}, \alpha_{\text{fatpad}}, \mu_{\text{muscle}}, \alpha_{\text{muscle}}$). The Ogden material model was chosen as it satisfies the principle of objectivity and contains response terms that are mutually orthogonal, meaning that the response terms are perpendicular to one another and have minimal covariance and are experimentally tractable [31,32]. In addition, for modeling simplicity the Ogden model assumes material isotropy. This has been recently demonstrated for the heel pad [17], and is a commonly used simplification for muscle and skin. It should be noted that the lumped toe tissue was not included in the optimization procedure and was assigned values of $\mu = 16.45$ kPa, and $\alpha = 6.82$, which were constant in all simulations.

In this study, the inverse FE analysis focused on determining the material coefficients that would result in the least difference between predicted and experimental deformations of the subject's forefoot. The differences in deformation were evaluated through the use of an objective function that compared the deformations predicted by the FE model with the deformations observed in the MRI images.

To quantify the difference between predicted and experimental deformation the following procedure was developed: In the initial step, both the unloaded and loaded MRI image sets were recolored into four categories of homogenous tissue sections representing skin, fat, muscle, and bone (Fig. 4). A map of the location of the nodes in the undeformed FE model was then overlaid on the recolored images of the unloaded foot (Fig. 5(a)). The color value corresponding to the location of each FE node in the unloaded image

was then assigned to each individual node. FE simulations were then run incorporating all four loading conditions under static conditions using an initial guess to set the material coefficients of the soft tissues. In this case the skin, fat, and muscle were all assigned the same coefficients as an initial guess ($\mu = 16.45$ kPa, $\alpha = 6.82$) based on the work of Erdemir et al. [28]. Bone was assumed to be rigid. A map of the deformed node location for each loading condition was then created and overlaid on the recolored MRI images corresponding to that loading condition. The color value corresponding to the location of each node was identified and compared with the original color value assigned to that node based on its location in the unloaded images. If the deformation predicted by the FE model exactly matches the deformation observed in the MRI images then there should be no difference in the color value. Any difference in the color value indicates that the FE model did not successfully replicate the observed experimental deformation (Figs. 5(b) and 5(c)). To quantify goodness of fit between the result from the FE model and the experiential deformation, the following optimization function [Eq. (3)] was defined to take into account the differences in color values for each node at all loading conditions:

$$E = \sum_{f=1}^4 \sum_{n=1}^m (I_{n,0} - I_{n,f})^2 \quad (3)$$

where E is the square of the total difference in color values, $I_{n,0}$ is the undeformed color value at node n with zero load applied (undeformed condition), and $I_{n,f}$ is the color value at node n 's deformed coordinates in the image set with load f applied. Values of I were set as 0, 0.5, and 1 for fat, muscle, and skin, respectively. The total difference is a summation of the differences at each of the four simulated experimental load conditions ($f \in [12.5\%, 25\%, 37.5\%, 50\% \text{ body weight}]$). The inclusion of intermediate loads, rather than just the maximal load, allowed for better determination of the nonlinear history of the deformation. Nodes were

Fig. 4 An exemplar slice from the undeformed MRI image set (a). The same slice showing the segmentation of structures; red denoting skin, blue, fat pad, and green, bone, where all remaining tissue was classified as muscle (b). The recolored ternary image based on the segmentation of structures (c). It should be noted that the tissue on the dorsal side of the foot was considered to be either muscle or skin only to ease in the construction of the FE mesh as this simplification did not impact the results of the FEM model prediction of plantar pressure.

Fig. 5 A schematic description of the mesh overlay process in the region of interest shown at the top. (a) Each node of the undeformed FE mesh is assigned a pixel intensity value corresponding to its location in the undeformed MRI image set. This pixel value is fixed to the node as it undergoes deformation during simulation of the experiment. The deformed mesh can be used to generate a (relatively coarse) node-predicted deformed image that can be compared to the experimental MRI images on a node by node basis. (b) If the current material coefficients are, for example, stiffer than the real material, then the mesh will not deform as much as the tissue and the node intensity values will fail to correlate with the deformed MRI image set. (c) If the material properties governing node motion correctly match the tissue, then the deformed mesh will correlate well with the deformed image set. Although this process is shown here in 2D with 8 nodes, the technique was applied in 3D allowing for out-of-plane deformations of more than 17,000 nodes induced by nearly incompressible materials.

excluded from the error calculations if their deformed coordinates caused the nodes to be located outside of the three-dimensional bounding box that defined the volume over which MRI images were obtained.

This occurred at the proximal cut surface of the model where the soft tissue bulged beyond the plane of the most proximal MRI image. This resulted in exclusion of up to a maximum of 250 nodes (1.4% of all nodes) from this area of low interest in all of the simulations run in this study. FE nodes located in the toes also were not considered in the optimization, all other nodes ($m \sim 17,450$ nodes) were included in error calculations.

After completion of the initial simulation and the initial calculation for the optimization function using the starting coefficients listed in row 4 of Table 1, numerical gradients in parameter space were calculated for each of the six material coefficients (requiring an additional six FE solutions). Once the numerical gradients were defined, the material coefficients were updated using a custom gradient-based optimization algorithm. The optimization took controlled steps along the gradient in the direction of steepest descent using a golden section-based line search [33]. This procedure was iterated until a minimum in the optimization function was realized, i.e., the function value did not decrease any further. It should be noted that in order to account for the near incompressibility of the soft tissues during the optimization simulations it was necessary to adjust the coefficient D as μ changed, in each iteration to ensure that the effective Poisson's ratio (ν) remained unchanged ($\nu = 0.475$). The α and μ assigned to each tissue layer during the simulation that achieved this minimum were considered the optimal values that would provide the closest approximation to

experimentally measured tissue deformation. An overview of the optimization process is presented in Fig. 6.

To verify that the minimum obtained from the initial optimization procedure could not be improved upon, the procedure was repeated using four different starting points. The first two repetitions of the optimization procedure perturbed the original material property values by decreasing or increasing the stiffness of the material by altering the value of the initial starting coefficients by one standard deviation as determined from a bulk heel pad study [28] ($\mu \pm 8.27$ kPa, $\alpha \pm 1.57$). The initial coefficients for the more compliant starting point are listed in Table 1 row 5 and initial coefficients for the stiffer starting point are listed in Table 1 row 6. If a reduction in the optimization function was realized when the optimization process was run with these new starting points, then the optimization process would be repeated using an additional two starting points. The starting points for this optimization would be defined by decreasing or increasing the stiffness of the coefficients that were identified to result in the new minimum of the objective function (rows 7 and 8 of Table 1). If no further reduction in the objective function was realized by restarting the optimization procedure with these perturbed starting points, then the minimum value of the optimization function obtained through this process would be considered the best local minima and the coefficients utilized in the simulation that produced this minima would be considered the optimal coefficients to best predict tissue deformations.

Once the material property coefficients that yielded the best local minima of the objective function were identified with no decrease in the objective function being realized following perturbations of

Table 1 Summary of optimization results to identify material coefficients of foot tissues^a

Lumped tissue representation ^b															
	Starting coefficients						Optimized coefficients						%ΔE		
	μ (MPa)	α	E	μ (MPa)	α	E									
1	0.01645	6.82	26,030	0.02652	17.71	20,880	−19.8								
2	0.00818	5.25	28,003	0.02652	17.73	20,880	−25.4								
3	0.02472	8.39	22,729	0.02660	17.68	20,880	−8.1								
Layered tissue representation															
	Starting coefficients							Optimized coefficients							%ΔE
	μ _M (MPa)	α _M	μ _S (MPa)	α _S	μ _F (MPa)	α _F	E	μ _M (MPa)	α _M	μ _S (MPa)	α _S	μ _F (MPa)	α _F	E	
1	0.01645	6.82	0.01645	6.82	0.01645	6.82	26,030	0.05051	31.44	0.03254	22.76	0.01765	3.31	20,095	−22.8
2	0.00818	5.25	0.00818	5.25	0.00818	5.25	28,003	0.03349	17.92	0.01596	22.74	0.03780	5.51	20,755	−25.9
3	0.02472	8.39	0.02472	8.39	0.02472	8.39	22,729	0.04018	24.10	0.03167	22.75	0.02032	5.33	20,408	−10.2
4	0.04224	29.87	0.02427	21.20	0.00938	1.74	22,189	0.04366	32.75	0.02416	22.68	0.01800	1.87	20,104	−9.4
5	0.05878	33.01	0.04081	24.34	0.02592	4.88	21,161	0.05737	28.82	0.04057	22.71	0.01653	−0.77	20,090	−5.1

^aInitial estimates for material properties were adapted from Erdemir et al. [28] based on the mean and 1 standard deviation reported for lumped heel pad. Three analyses were conducted for lumped tissue representation of the forefoot and five for the layered tissue representation. Additional simulations for the layered tissues included a perturbation study in a region that appeared to include a global solution. Both starting and final values for the material coefficients are reported, along with the improvement in the objective (fit error). Best fit with minimum final error are bold. μ , α : material coefficients [see Eq. (1) for the description of the material model]; M: muscle; S: skin; F: fat; E : fit error; and % ΔE : percent change in fit error from starting point of the optimization.

^bNote: Bone was modeled as a rigid material.

Fig. 6 Schematic diagram of the inverse finite element technique used to determine material coefficients. Inputs to the technique (at the left) are deformed and undeformed MRI image sets, undeformed FE mesh, and an initial guess for material coefficients. The mesh overlay process, used to determine the pixel value at each node, is further described in Fig. 5. The error calculation and its inputs are described with Eq. (3). Briefly, each vector $I_{n,f}$ contains the corresponding image intensities for each of the n nodes at loading level f . Error is calculated by comparing predicted intensities at each of the loading levels to the intensities in the unloaded state $I_{n,0}$.

the optimized coefficients, a sensitivity analysis was run to determine the effect of the values of the individual coefficients on predicted model behavior. In this analysis, each optimized coefficient was varied by $\pm 10\%$ requiring the solution of an additional 12 models. The effect of altering the individual coefficient values was evaluated by comparing compressive strains predicted at representative points within the three layers (skin, fat, muscle) between the second metatarsal head and the floor.

As discussed previously, a common simplification applied to many foot models is for all the plantar soft tissues to be assigned a single set of material properties (the lumped parameter model). To evaluate if the utilization of discrete soft tissue layers would

result in improved model performance, the above described optimization procedure was also performed on a model using a lumped parameter description for all plantar soft tissues. The results of the tissue layer model and the lumped material model were evaluated by comparing the error associated with each model when optimized coefficients were used to define the respective material properties [1,34]. These results are shown in Table 2.

To evaluate the effect of mesh density on the strains predicted by the model, the optimized material coefficients were incorporated into the forefoot model under conditions more representative of gait, and a simple mesh sensitivity test was conducted using a finer mesh (39,675 elements). Both the coarser mesh model and

Table 2 Summary of sensitivity analysis relating effect of tissue coefficients to nominal strains predicted by the model^a

Coefficient perturbed	% Perturbed	% Change in nominal strain in skin layer	% Change in nominal strain in fat layer	% Change in nominal strain in muscle layer
Skin μ	-10.0	13.7	0.01	-0.10
Skin μ	10.0	-11.1	-0.03	0.08
Skin α	-10.0	3.07	0.00	-0.08
Skin α	10.0	-2.71	0.06	0.12
Fat μ	-10.0	-2.03	2.85	-0.52
Fat μ	10.0	3.41	-2.68	0.43
Fat α	-10.0	3.56	4.56	-2.02
Fat α	10.0	-1.71	-4.32	1.81
Muscle μ	-10.0	0.38	-0.06	3.62
Muscle μ	10.0	0.70	0.04	-3.19
Muscle α	-10.0	-8.26	-1.28	5.26
Muscle α	10.0	11.0	1.40	-6.32

^aA total of 12 simulations were run in which each material coefficient was varied by $\pm 10\%$ to evaluate the sensitivity of the predicted nominal strain to boundary conditions.

the finer mesh model were evaluated by running a simulation in which the joints of the foot were fixed and a 485 N vertical load was applied to the dorsal surface of the forefoot model, while the plantar surface of the foot was modeled as being in contact with a rigid surface. A coefficient of friction of 0.5 was assigned to the contact between the plantar surface of the foot and the rigid surface. In this case the models were evaluated by comparing compressive strains predicted under the bony prominence of the second metatarsal head at the approximate midpoint of the muscle and fat layer, and at the foot-floor interface in the case of the skin layer in both models. A comprehensive mesh sensitivity analysis was not performed due to large time commitment associated with generating hexahedral meshes for geometrically complex structures such as the foot. In this study, the coarse mesh was utilized for the inverse FE analysis due to the large number of parametric runs necessary to optimize the material properties of the various layers. The large number of parametric runs dictated that solution times should be as short as possible to allow for the optimization problem to be solved within a reasonable amount of time.

The coarse meshed model used in the mesh sensitivity analysis was also used to evaluate the differences in the mechanics predicted when individual tissue layers were incorporated in the model and when a lumped material model was used to define the material properties of the soft tissue. The resulting models were compared based on the von Mises stresses and the maximum principal strains predicted in the region under the metatarsal heads and the plantar pressure predicted by each model.

Results

During the optimization process, more than 250 finite element solutions with different material properties were obtained. The average model solution time was 5 h on a computer with two, dual-core, Xeon[®] processors running 64-bit Red Hat Enterprise Linux with 6 GB of RAM. If relatively small improvements in error [defined in Eq. (3)] from different starting points to the optimized points were encountered, this would imply that the starting points represented good initial guesses. Nonzero final errors would imply that there were systematic modeling errors that could not be resolved by changing the material parameters. In general, the optimization was more sensitive to α coefficients than to μ coefficients as expected from the Ogden material model definition where the α terms are raised to the second power [see Eq. (1)].

Layered Tissue Model Optimization. A total of five optimization procedures were run to optimize the material coefficients of the tissue layer model each employing a different starting point, the results of which can be seen in Table 1. The initial optimization procedure utilized a starting point where the skin, muscle, and fat were initially assigned the same coefficients. This initial

optimization procedure was successful in reducing the objective function from an initial value of 26,030 to 20,095 yielding an initial set of optimized coefficients as listed in Table 1. To determine if the value of the objective function calculated utilizing the deformations predicted by these optimized coefficients represented a global minimum, the optimized coefficients were perturbed by ± 1 standard deviation of the coefficients published by Erdemir et al. [28] resulting in objective function values of 20,408 and 20,755 when the starting coefficients were increased or decreased, respectively. As neither of these two starting points yielded a lower value for the objective function, the optimized coefficients obtained from the initial optimization procedure were perturbed by the same standard deviation values and set as the initial values for the start of an additional two optimization procedures. Using the reduced optimized coefficients as a starting point resulted in an optimized objective function value of 20,104, while a starting point using the increased optimized coefficients yielded an optimized objective function value of 20,090. As this was the lowest value of the objective function achieved, the associated coefficients were considered to represent the global minimum. Figure 7 provides a qualitative comparison of FEM predicted deformation in the region of the metatarsal heads of the deformations using optimized coefficients with

Fig. 7 Qualitative comparison of the deformations predicted in the region of the metatarsal heads when a compressive load equal to 50% body weight was applied to the model versus deformations observed in MRI images when the equivalent load was applied to the imaged forefoot

Fig. 8 Overall deformation (nominal strain, bottom row) of the forefoot at full 50% BW loading using optimized coefficients for layered tissue representation (best fit, see Table 1 for coefficients), along with hydrostatic pressure (middle row), and von Mises stress distribution (top row) within tissue layers. The loading and boundary conditions were representative of the MRI experimentation. The forefoot model was sectioned at an approximate level of metatarsal heads to emphasize a potential region of clinical interest. Distributions of all strain components illustrate the complex nature of the combined deformation modes in the foot. See text for further discussion.

those observed in the MRI images. Figure 8 illustrates the overall qualitative deformations, von Mises stresses, hydrostatic pressures, and nominal deformation predicted by the FE model when the optimized coefficients were incorporated.

Lumped Tissue Model Optimization. A similar procedure was run in which all of the soft tissues were modeled as one material. The results of this optimization procedure are also detailed in Table 1. It is interesting to note that no matter what starting coefficients were utilized, the optimization procedure always returned very similar coefficients and identical minimal values of the objective function (20,880), indicating that the process converged to the same location in the solution space. It should be noted that the optimized value of the objective function for the lumped parameter models was greater than the value of the optimized objective function when the skin, muscle, and fat were modeled as individual layers, indicating that the layered model was more successful in replicating the experimentally observed deformations of the forefoot.

Sensitivity Analysis. The sensitivity analysis indicated that variations of 10% in the Ogden material coefficients assigned to each tissue layer had variable impact on the compressive nominal strains predicted by the model in the tissue layers under the second metatarsal head as detailed in Table 2. The greatest change in the predicted nominal strains was 14% which occurred in the skin layer and resulted from decreasing the μ parameter of the skin by 10%. Overall, the sensitivity analysis indicated that varying the μ parameter assigned to the skin layer resulted in the greatest changes in the nominal strain, whereas varying the material coefficients assigned to the fat layer had the least impact on the predicted nominal strain. It was also interesting to note that varying

the material coefficients of one layer could have a larger impact on the nominal strain predicted in another layer than on the nominal strain predicted for the altered layer. For example, when the α parameter for the muscle layer was increased by 10%, an 11% increase in the nominal strain was predicted in the skin layer, whereas only a -6% change was observed in the nominal strain in the muscle layer.

Sensitivity to mesh density was explored by solving the mesh used in this study and a higher density mesh under the same loading conditions and observing differences in the compressive strains within the layers perpendicular to the floor. For all materials, the finer mesh predicted stiffer material responses resulting in strain differences of 0.60%, -0.15%, and -97% in muscle, fat, and skin layers, respectively. The high percentage change in strain in the skin layer is likely due to the small magnitude of the skin strain (coarse model skin strain = -1.31×10^{-2} , fine model skin strain = -4.40×10^{-4}) and the change from one to two elements across the skin's thickness. As seen in Fig. 9, mesh density had minimal impact on the von Mises stresses and contact pressures with both models predicting similar distributions and magnitudes for both parameters when the optimized material coefficients were assigned to the tissue layers. It should be noted that the wall clock time to solve the finer mesh was 2.4 times higher than the original coarse mesh (~6 h versus ~2.5 h).

Qualitatively similar distributions of plantar pressure were predicted by a model incorporating layered tissue material properties and a model incorporating lumped tissue material properties (Fig. 10). However, the model incorporating the lumped material properties for the soft tissues predicted larger magnitudes of plantar pressure, probably a result of the whole system being stiffer than the model incorporating layered material property definitions. As expected, the distributions of von Mises stresses and maximum principal strains were uniform in the lumped material

Fig. 9 Clinically relevant mechanical variables were not highly sensitive to increased mesh density. While a coarser mesh was used for the identification of material coefficients (left: 26,335 elements, 29,697 nodes), a higher mesh density may be desirable for convergence (right: 39,675 elements, 43,893 nodes). Plantar pressures and von Mises stress distribution are plotted. Both the magnitude and location of peaks were similar between the predictions of coarse and fine meshes as obtained by using the best material coefficient fit (see Table 1 for coefficients). Loading and boundary conditions of these simulations approximated those of peak forefoot loading instant of the push-off phase.

model. The layered material model predicted that the soft fat pad layer had larger deformations than the stiffer muscle and skin layers while exhibiting lower stresses (Fig. 10). It is of interest to note that the highest levels of von Mises stresses were located under the third metatarsal head in both the layered tissue and lumped tissue model. However when comparing maximum principal strains, the lumped model predicted the greatest deformations to occur under the third metatarsal head, whereas the layered tissue models indicated that the greatest deformations would occur in the fat pad under the first metatarsal head (Fig. 10).

Discussion and Conclusions

In this study the inverse finite element method was used to optimize nonlinear hyperelastic material coefficients to minimize the difference between displacements predicted by an FE model of the forefoot and those observed experimentally. To accomplish this the MRI images of the forefoot were acquired and recolored so that the discrete structures of the foot (bones, skin, fat pad, and muscle) were all represented by a single color with white representing skin, gray, muscle, and black, fat pad. The bones were also colored black as they were completely surrounded by muscle. In terms of gray scale this resulted in a ternary colored image with pixels representing bones or fat pad having a value of 0, pixels representing muscles having a value of 0.5, and pixels representing skin a value of 1. The nodes of the FE model corresponding to each structure were also assigned the corresponding color values. This allowed us to define an optimization function that would quantify how well the deformations predicted by the FE model matched those measured in the MRI images by comparing color values assigned to the nodes with the color values assigned to the corresponding pixel in the MRI image. The drawback to using ternary recolored images for this process is that the optimization function becomes more sensitive to difference in displacements occurring at the borders of the

structures and, unless large deformations occur, insensitive to differences occurring away from the structures borders. However, in spite of this limitation, an error is still generated by differences in predicted and measured deformations occurring at the borders of the structures which can be minimized, thereby increasing the agreement of the deformation predicted by the FE models with the deformation measured in the MRI images. A one-dimensional analogy of this approach is related to estimation of spring parameters for three springs arranged in series, e.g., representing muscle, fat, and skin. If only the location of bone-muscle insertion and ground-skin point is tracked, one can only estimate a lumped stiffness parameter (rather than individual stiffness parameters for muscle, fat, and skin). If one can also track the point at the muscle-fat, and fat-skin interface, it will be possible to calculate stiffness parameters for all.

An additional limitation of the proposed method is that the segmentation of different tissue types is difficult to perform without operator intervention and thus there is a subjective component to the identification of the tissue regions. One of the authors segmented the slice shown in Fig. 4 on three separate occasions and obtained estimates for the tissue area that varied by 0.53% for muscle, 2.5% for fat, 1.8% for bone, and 7.8% for skin (values represent the average percent deviation from the mean). This suggests that measurement of bone, muscle, and fat areas are reasonably reliable but that the values for skin should be considered to be only an approximate estimate. The model results should be interpreted in light of these errors in segmentation.

In spite of the optimization of the assigned material coefficients, the value of the objective function quantifying the error in the predicted displacement could not be reduced to zero. Differences between model-predicted deformation and the experimental deformation may come from two sources: improper material coefficients and errors in modeling assumptions. The material coefficients determined to minimize the difference between predicted and

Fig. 10 Comparison of clinically relevant mechanical variables predicted when tissue layer material properties were incorporated in the model (left) and when lumped material properties were used (right). Top row illustrates similar predicted plantar pressure distributions in both models. However, the lumped material model predicted higher magnitudes of pressure. Middle row illustrates the comparison of von Mises stresses in the region under the metatarsal heads. While stresses are concentrated under the third metatarsal head in both models, stress distribution is more uniform in the lumped model (right) than in the layered model (left) where reduced levels of stress are observed in the highly compliant fat pad tissue layer. Bottom row illustrates the comparison of maximum principal strains in the region under the metatarsal heads. Peak strain values were concentrated under the first metatarsal head in the layered model (Left) and under the third metatarsal head in the lumped model (right). Strain distribution was more uniform in the lumped model (right) than in the layered model where high strain values were observed throughout the highly compliant fat pad layer.

experimentally measured tissue deformation were found through the minimization of an objective function. In an ideal situation these coefficients would predict deformations that would result in a global minimum of the objective function being obtained. In this work a gradient-based optimization algorithm was used to find the minimum. The drawback to this method is the minimum found is dependent on the starting point. In this study the starting point was based on experimental data and examined a parameter space consistent with this data, however, it cannot be claimed that the entire parameter space was examined; therefore, the minimum obtained cannot be considered to be the global minimum. Nonetheless, based on the available information in the literature, we feel that the starting point chosen and the parameter space explored were the most appropriate for determining physiologically relevant values for the material coefficients.

The modeling errors may include: (1) simplification of geometry; (2) lumping of tissues; and (3) inadequacy of the chosen material model. The Ogden material model has been shown to fit soft tissue mechanical behavior well, i.e., with a low rms error, and with relatively good efficiency, i.e., only two coefficients. It has also been reported to be more accurate than other models in fitting experimental results when data from multiple deformation modes are available [35]. Two disadvantages to the Ogden model are that

it cannot account for the viscoelastic properties of tissue stand-alone and that it cannot be expanded easily to include material anisotropy. Both of these limitations are likely to be important for skin and muscle which have been characterized as visco-hyperelastic anisotropic materials. The difficulty in incorporating visco-hyperelastic materials and anisotropy into a model like the one presented here stems from the complexity involved with incorporating both properties. To incorporate the visco-hyperelastic material in a manner similar to that presented in a recent work by Natali et al. would require the definition and optimization of nine parameters for each material modeled as visco-hyperelastic [36]. Incorporating anisotropy further complicates the model especially in the case of muscle. In the method proposed by Sharafi and Blemker for incorporating anisotropy into the model, each muscle of the forefoot would have to be incorporated as a discrete structure in order to accurately account for the fiber orientation of each model [37]. Incorporating both methods in a forefoot model would result in a very computationally expensive model that would be difficult to solve and to optimize in the manner presented here. In addition, the experimental deformation data that was used in this study was obtained under quasi-static conditions which were necessary for acquiring the MRI images and this precludes the estimation of both long term and short term

time constants which would be necessary to incorporate the visco-hyperelastic material model. As a result, due to the quasi-static nature of the experimentation, estimated coefficients for a visco-hyperelastic model may not have any practical meaning.

A further limitation of the Ogden model stems from the fact that despite using different coefficients similar values of the objective function were obtained. However, it should be pointed out that the ultimate goal of foot modeling, and the underlying representation of materials, is to evaluate peak stresses-strains within the whole foot and within the individual tissues. If different material coefficients still provide similar results in terms of these variables, then their unique determination may not be critical to obtaining useful and accurate predictions of the mechanics of the foot.

In spite of the above listed limitations, the Ogden material model has been shown to be capable of effectively modeling the structural response of the heel pad. Chokhandre et al. have demonstrated this by achieving accurate predictions of the force displacement relationship in their model of heel pad when compared to the relationship measured in a cadaveric foot [38]. However, it should be noted that in this model the tissues of the heel pad were modeled as a single tissue using one set of material properties to describe the mechanics of all tissues. Due to the difficulties in validating the behavior of the individual tissue layers, we cannot guarantee the accuracy of the Ogden material model in predicting the mechanics of the individual tissues. However, we have shown that the tissue layer model can successfully replicate the deformations forefoot when the predicted displacement are compared to those measured experimentally.

The inverse FE analysis technique described in this investigation is unique in that the experimental strains are not known for comparison with the model predictions. Instead, matching of experimental strains is implied by agreement between the model predicted and experimental image sets. This method eliminates the need to track strains in three dimensions but requires a good initial guess to be effective. An alternative technique would be to use hyperelastic non-rigid image registration to calculate experimental strains from the MRI image data (e.g., [39]). Although hyperelastic registration is a promising method of tracking 3D strains in MRI foot images, software to perform this type of analysis is not currently available commercially or otherwise.

Subject-specific material properties were successfully optimized from *in vivo* MRI load-deformation data. Using data of this type has several distinct advantages for material parameter optimization. First, the testing is truly *in vivo* and is not subject to the issues of tissue hydration, temperature, viability, sample edge boundary conditions, or animal model extrapolation to humans. Second, the ability to examine individual tissue layers in three dimensions with intact connections to neighboring layers is maintained. Third, although only a compressive load was applied, the irregular, nonlinear geometry resulted in a combination of compressive, tensile, shear, and volumetric loading within the tissue. As a result, parameter optimization included information about material response to a variety of deformation modes likely to be encountered during gait simulations. For a similar Ogden-based elastomeric foam material model, the inclusion of multiaxial test data during parameter determination was shown to be important for predicting deformations in complex loading simulations [40]. The one drawback to this approach is that an assumption regarding material behavior must be made *a priori* in order to utilize the inverse finite element method in that a material model must be chosen. As a result, this method optimizes that particular material model to obtain the most accurate deformation predictions possible rather than characterizing the material by defining a material model based on experimentally observed deformations. The latter approach requires exhaustive experimentation to fully define a material model [32].

The inclusion of skin, fat, and muscle tissue layers in a 3D finite element foot model represents a significant increase in complexity over the current state of the art. However, this is still a simplification of a complex anatomical structure and future models should attempt to include more tissue components. The model used in

this investigation explored the current limits of the ABAQUS[®] Standard FE solver by including nonlinear geometry, nonlinear materials, confined compression of nearly incompressible tissue, and contact with friction. As computational power increases and FE solver efficiency and capabilities expand, it will be possible to increase the complexity of the model by including cartilage, tendons, ligaments, joint capsules, and/or any other structure of interest that is visible in the high-resolution image sets.

A comparison of the plantar pressure, von Mises stresses, and maximum principal strains in a model incorporating different material properties for the individual tissue layers and a model using lumped material properties (Fig. 10) illustrates the potential benefits of using a more detailed layered tissue model. The layered tissue model shows that the highest stresses occurred in the muscle layer just under the third metatarsal head, whereas the largest strains occur within the fat pad under the first metatarsal head. The lumped material model predicted a similar location for the peak stresses but the details regarding the location of higher strain values could not be duplicated. The findings of the layered tissue model also raise an interesting question in terms of which parameter is more important with regard to the identification of potential locations for the development of diabetic foot ulcers. If one assumes that regions of high stress are indicators of ulcer risk, then both the layered and lumped model indicate that the region under the third metatarsal head is a region of high risk. However, if regions of large deformation are assumed to be indicators for ulcer risk then the two models differ in their predictions.

The sensitivity analysis presented in this study demonstrates the importance of material property assignment in this model of the forefoot and in future models. The sensitivity analysis illustrated that even minor variations ($\pm 10\%$) can have rather large impacts on the predicted nominal strain (differences up to 14%) in a given tissue layer. The sensitivity analysis also indicated that the assignment of material properties is important for each structure contained within the model, as altering the material properties of one tissue structure in this case resulted in changes of up to 11% in the nominal strain predicted in another tissue layer.

Completion of the over 250 simulations required for the current optimization consumed over 7 weeks of wall-clock time on a well-equipped personal computer. Although this process resulted in only one set of material coefficients, these coefficients significantly increase the predictive power of the 3D finite element forefoot model. The model may now be used with increased confidence to predict clinically interesting, and previously inaccessible, quantities such as plantar shear and internal tissue stress distributions during gait. For example, Fig. 8 shows major concentrations of stress at the bone/tissue interface regardless of material description.

Unfortunately, while the data presented in Fig. 8 are useful for illustrating the marked differences in internal stress that can result from using different material coefficients, they are not likely to be representative of the internal stress distribution during gait because the complexity of the internal anatomy is still not represented by the four-material representation employed here. Further work to verify and explore these internal relationships under gait-like internal loading is needed.

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