Body Mass Classification from Skeletal Elements Using Landmark-Free Morphological Atlas Estimation with Diffeomorphic Shape Mapping

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ABSTRACT

Purpose: We investigate whether femur morphology is affected by body mass (BM). To establish deformations associated with obesity, we propose an atlas estimation framework based on diffeomorphic shape mapping that relaxes the point correspondence requirement common to many conventional shape modeling approaches.
Methods: The study sample consisted of femora from 18 normal (BMI between 20-25) and 18 obese (BMI > 30) individuals (Texas State University Donated Skeletal Collection). Bone surface models (2,500 vertices and 5,000 faces) were generated from CT scans of the specimens (512x512 matrix, 0.625x0.625x0.5 mm voxels). The surface models were input to an optimization algorithm that yielded an atlas representation of shape variability consisting of a mean bone template and diffeomorphic deformations matching the template onto each specimen. The accuracy of normal vs. obese classification using principal atlas deformation modes was established in leave-one-out experiments with Support Vector Machine (SVM) classifier.
Results: We achieved 75% classification accuracy in leave-one-out SVM experiments, indicating the possibility of functional skeletal adaptations to increased body mass. By visualizing the bone surface deformation given by the SVM classification direction, we found that morphological alterations associated with obesity might include relative thickening of the femoral neck and the trochanters, and retroversion of the femoral head.
Conclusions: The landmark-free atlas estimation algorithm enabled detection of morphological femur variants that might be predictive of elevated body mass.

Keywords: Statistical shape models, large diffeomorphic deformation metric mapping, body mass estimation, morphological analysis, forensic anthropology

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1. INTRODUCTION

Bone functional adaptation theory indicates that elevated body mass (BM) should be reflected in morphological changes in weight-bearing skeletal elements. However, such alterations have not yet been characterized in detail. A quantitative understanding of possible bone shape variants associated with increased BM would be particularly important for forensic anthropology to enable the estimation of body mass (BM) of unidentified skeletal remains.
We report on the application of advanced 3D statistical shape analysis methods to detect morphological correlates of obesity in human femur. We propose to use an atlas estimation algorithm based on large diffeomorphic deformation metric mapping (LDDMM)[1] to represent the population shape variability as a set of transformations between a common template and each of the study specimens. Importantly, the mappings are found without invoking any point correspondences between the femoral surfaces in the population, thus relaxing a requirement common to many conventional shape analysis methods.

2. METHODS

2.1 Dataset Acquisition and Processing

The study involved femora from 40 males (Texas State University Donated Skeletal Collection), with 20 specimens obtained from individuals who lived with BMI between 20-25 (normal weight) and 20 obtained from individuals with BMI > 30 (obese). After excluding two specimens from each class from analysis because of significant bone surface erosions, the sample size was N=36 bones, 18 normal and 18 obese. The femora were imaged on a Canon Aquilion Precision ultra-high resolution CT at 0.5 mm slice thickness (512x512 matrix, 0.625x0.625x0.5 mm voxels). Triangulated surface models (2,500 vertices and 5,000 faces) of the bones were generated from the DICOM CT stacks in MATLAB 2021b, followed by isotropic remeshing and normalization in MeshLab 2021.07.

2.2 Atlas Estimation

To identify morphological variants associated with obesity, we represent the study population using an atlas consisting of (i) a template (mean) femur surface and (ii) transformations (deformations) mapping the template onto each sample.

The atlas transformations in (ii) are modeled using the LDDMM framework.[1] Specifically, the deformations are obtained as diffeomorphisms in R^3 given by flowing an integrable time series of vector fields $v(t,x), t \in [0,1]$, of R^3 with initial condition $\varphi^v(0,x)=x$:

$$\varphi^v(t,x)=x+\int_0^t v(s,\varphi(s,x))\,ds. \tag{1}$$

We can associate such transformations with a cost metric given by:

$$E(v)=\int_0^1 \|v(t,\cdot)\|_V^2\,dt, \tag{2}$$

where $\|\cdot\|_V$ denotes a spatial regularity-enforcing norm on the space V of vector fields.

The atlas estimation can now be summarized as follows: starting from a hypertemplate S_0 (typically a randomly chosen surface from the population), find a template $\bar{S}$ that is a diffeomorphic transformation of the hypertemplate together with transformations $\{v_i \vee i=1,\ldots 36\}$ that match the template to each sample (indicated by index i) from the dataset. This pipeline, shown in Fig.1, is formulated as an optimization problem using the previously defined deformation cost $E_S(v)$:

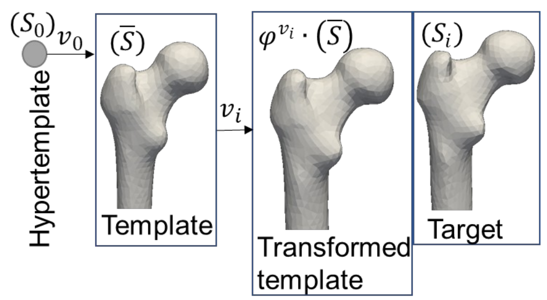

Fig. 1 The atlas estimation procedure. Starting from an initial hypertemplate (one of the study subjects), the algorithm iteratively evolves the template together with deformation fields v_i that approximately match the template onto the study subjects using landmark-free fidelity metrics.

$$\min_{v_i, i=0,\ldots 36} E(v_0)+\sum_{i=1}^{36} E(v_i)\; subj.\left\{\begin{array}{l}\bar{S}=\varphi^{v_0}\cdot(S_0),\\ \varphi^{v_i}\cdot(\bar{S})\approx(S_i)\end{array}\right. \tag{3}$$

where $\varphi^v\cdot(S)$ means applying the deformation φ^v to shape S. The (approximate) matchings between the transformed template and the datasets S_i written as $\varphi^{v_i}\cdot(\bar{S})\approx(S_i)$ are measured through a relaxation fidelity metric that does not require vertex correspondences (see Refs. 2 and 3).

Further details of the landmark-free atlas estimation framework can be found in Ref. 4. The implementation was based on the FshapesTk MATLAB library[5] and ran using its CUDA subroutines to accelerate computations.

2.3 Obese vs. Normal Classification using Atlas Transformations

After atlas estimation, the morphological variability in the study sample is encapsulated in the Gram matrix of atlas deformations G = $(\langle v_i, v_j\rangle)_{i,j=1,\ldots 36}$:

$$\langle v_i, v_j\rangle \doteq \int_0^1 \langle v_i(t,\varphi(t,\cdot)), v_j(t,\varphi(t,\cdot))\rangle_V\,dt. \tag{4}$$

Principal components (PCs) of shape variations are obtained by Singular Value Decomposition (SVD) of the Gram matrix.

To identify femoral morphology associated with obesity, we performed leave-one-out classification experiments: each bone was classified as obese or normal by applying Support Vector Machines (SVM) trained on PC decompositions of the remaining bone surfaces. To find the optimal PC reduction dimensionality, we repeated the experiments by increasing the number of PCs used to represent femur shape in order of decreasing explained variance (ranging from the 1st PC to all 36 PCs).

After establishing the number of PCs that yield the highest leave-one-out classification score, the morphological deformation associated with obesity was identified as the normal of the SVM separating hyperplane in the space span by those PCs. By transforming the template $\bar{S}$ parallel/antiparallel to the normal vector, we were able to visualize shape changes representative of obese/normal phenotypes.

We compared the performance of the above dimensionality reduction and classification procedure using either the entire surface of the femur or only its proximal section (femoral head, approx. the top 1/3 of the length of the bone).

3. RESULTS

	Classified as Obese	Classified as Normal
Entire femur		
Obese	11	7
Normal	3	15
Proximal femur		
Obese	11	7

SVM on shape variation modes of the entire femur yielded the highest classification accuracy of 75% using the first 3

PCs. The accuracy remained near 70% ($\pm 5\%$) for SVM experiments including more than 3 PCs. Classification on the proximal section of the femur achieved 75% accuracy using the 6 most significant PCs. This could be improved to 80.6% by including the first 30 PCs; however, such large number of PCs might indicate possible overfitting and therefore we focus the subsequent analysis on a conservative choice of 6 PCs. The confusion matrices for the two classifications are shown in Table 1. The accurate classification performance indicates that body mass does indeed impact femoral morphology and that these deformations can be detected using the landmark-free atlas estimation algorithm. Fig. 2 shows the template deformed along the classification direction of the SVM obtained for the optimal number of PCs discussed above. Compared to normal variants, the transformation towards bone morphology associated with obesity appears to involve: (i) relative thickening of the femoral neck and the trochanters, (ii) retroversion of the femoral head, (iii) slightly more vertical orientation of the intertrochanter crest, and (iv) relative thickening of the femoral shaft. The variations detected in the proximal femur are similar for classifications based on the entire bone surfaces and based only the femoral head region. The comparable classification accuracy of the two approaches suggests that morphological alterations in the proximal femur likely dominate the obesity-related deformation.

4. DISCUSSION & CONCLUSIONS

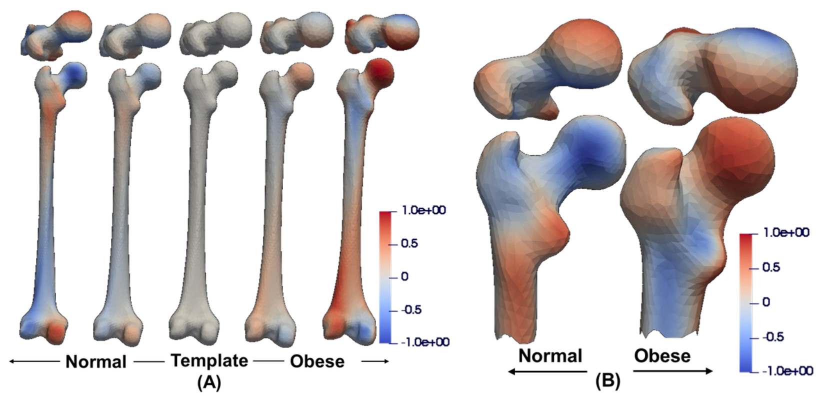

Fig. 2 Visualization of the deformation associated with obese vs. normal classification. By increasing the magnitude of the transformation applied to the template, the shape alterations indicative of body mass become more pronounced. Shape modes obtained from classification experiments on the entire femora are in (A), the experiments using only the proximal section are in (B). The first row in each case shows the top view of the template, while the second row shows its coronal view. Color indicates relative deformation from the template, positive/negative

This preliminary study in a male population indicates that obesity (BMI > 30) is associated with morphological alterations to the femur. To the best of our knowledge, this is one of the first results demonstrating such functional skeletal response to increased body mass. These findings contribute to our understanding of bone adaptation. Furthermore, automatic detection of shape deformations related to obesity might provide a new marker for identification of skeletal remains and matching of unknown and missing persons. An important innovation in this work is the application of an atlas estimation procedure based on diffeomorphic shape mappings that does not require *a priori* vertex correspondences between the study sample surfaces. This relaxes the point matching requirement common to many shape modeling approaches. Ongoing work includes comparison with standard landmark-based anatomical measurements and conventional landmark-based shape analysis, as well as extension to female samples and other weight-bearing skeletal elements.

5. ACKNOWLEDGEMENT

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