Developing Parametric Human Models Representing Various Vulnerable Populations in Motor Vehicle Crashes

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Abstract

Children, small female, elderly, and obese occupants are vulnerable populations and may sustain increased risk of death and serious injury in motor-vehicle crashes compared with mid-size young male occupants. Unfortunately, current injury assessment tools do not account for immature and growing body structures for children, nor the body shape and composition changes that are thought make female/aging/obese adults more vulnerable. The greatest opportunity to broaden crash protection to encompass all vehicle occupants lies in improved, parametric human models that can represent a wide range of human attributes. In this study, a novel approach to develop such models is proposed. The method includes 1) developing statistical skeleton and human body surface contour models based on medical images and body scan data using Mimics and a series of statistical methods, and 2) linking the statistical geometry model to a baseline human finite element (FE) model through an automated mesh morphing algorithm using radial basis functions, so that the FE model can represent population variability. Examples of using this approach to develop parametric pediatric head model, adult thorax and lower extremity models, and whole-body human models representing various populations were represented. The method proposed in this study enables future safety design optimizations targeting at various vulnerable populations that cannot be considered with current injury assessment tools.

Keywords: *Parametric Human Model, Injury Assessment, Vulnerable Population.*

1. Introduction

Even though vehicle safety designs have been significantly improved over the past half century, road traffic injuries continue to be a serious public health problem worldwide. Among the whole population, children, elderly, small female and obese occupants are at increased risk of death and serious injury in motor-vehicle crashes compared with mid-size young male occupants (Bose et al. 2011; Boulanger et al. 1992; Kent et al. 2005; Morris et al. 2002; Morris et al. 2003; Rupp et al. 2013; Zhu et al. 2010). Children are considered to be vulnerable in crashes because of their immature body structures; elderly are vulnerable because of their aging-related morphological and physiological changes; while obese occupants are vulnerable because of their increased mass and body shape induced poor belt fit. Unfortunately, none of these reasons is adequately addressed by the current regulated procedures for evaluating the occupant protection of vehicles. In particular, current child dummies are essentially scaled versions of the midsize-male adult dummy, and do not consider the anthropometric and biomechanical difference between an adult and a growing child. Current adult crash dummies and finite element (FE) human models only focus on a few body sizes (large male, mid-size male, and small female) and do not consider age effects and different body shapes. As a result, current injury assessment tools for adult cannot be used to evaluate the injury risks for elderly and obese occupants.

Due to increasing life expectancy and decreasing birth rates, the growth rate of older population is much faster today than in the past and it is expected to be even faster in the next several decades in the

US, Japan, China, and many other countries. By 2030, 20% of the US population will be age 65 or older (http://www.census.gov). Similarly, China will have 285 million people over the age of 60 by 2025, and the projected portion of China's population over age 65 will be more than 23% in 2050. The proportion of obese individuals in the US population has also increased significantly during the past two decades. In 2009-2010, 35.7% of the US adults were obese (Ogden et al. 2012), and by 2030 this rate would increase to at least 44% to 60% in the US. The projected increase of older and obese population in the US and China and the “One-Child” policy in China further motivate future efforts to develop more advanced injury assessment methodologies and tools to evaluate vehicle safety designs for mitigating injuries for these vulnerable populations.

There are several hypothesized reasons for the effects of human characteristics on injuries, including variations in bone geometry, cross-sectional area and material properties, body size, mass, and external body shape with gender, age, and body mass index (BMI). These variations affect injury occurrence and the directions and magnitudes of loading to the human body in collisions. The relative contributions of these hypothesized reasons for the effects of age, gender, stature and BMI on injury risks in crashes can best be assessed using a parametric human FE model, which can be morphed automatically. This FE model needs to have geometric, compositional and material characteristics that are parametric with age, gender, stature, and BMI. However, such a model does not currently exist. The automated procedure for developing parametric human models representing individuals with different characteristics will enable population-based simulations, and thus overcome the limitations in existing methods for safety designs that do not adequately consider human geometrical and biomechanical variability. This new design paradigm will have overarching impacts on not only the vehicle safety designs, but also other engineering designs interacting with human.

In the recent years, University of Michigan Transportation Research Institute (UMTRI) has developed an approach to parametric human FE modeling that allows the size, shape, and material parameters of an FE human model to be rapidly varied based on age, gender, stature, and BMI. This approach is being used to investigate the effects of age and obesity on human injury response in motor-vehicle crashes, because developing and validating the number of FE models needed for simulations to understand the effects of age and BMI on injury using traditional methods is prohibitively costly and time-consuming.

In this paper, we presented an overview of the UMTRI approach for building parametric human FE models that focuses on the development of statistical models of human geometry and the method used to rapidly morph a baseline FE model into geometries associated with different human parameters. Mimics has been used as the imaging segmentation tool to develop the statistical skeleton geometry models and quantify the geometry variation among the population. Summaries of the development of several parametric human FE models focusing on the geometry and mesh morphing are provided to illustrate the feasibility and effectiveness of our approach.

2. Materials and Methods

A schematic of our approach for developing a parametric human FE model is shown in Figure 1. The foundations of the parametric human model concept are statistical models of human geometry that describe morphological variations within the population as functions of human parameters (age, gender, stature, and/or BMI) and a mesh morphing method that can rapidly morph a baseline human model into other geometries while maintaining high geometry accuracy and good mesh quality. Stochastic descriptions of human material properties are also critical for model development and validation, however, these data are generally available in the literature (Burstein et al. 1976; Hu et al. 2011a; Kemper et al. 2005; Kemper et al. 2007; Lobdell et al. 1973; Takahashi et al. 2000; Wall et al. 1979; Yamada 1970) and therefore are not presented in this paper. Validation approaches are also discussed elsewhere (Hu et al. 2012).

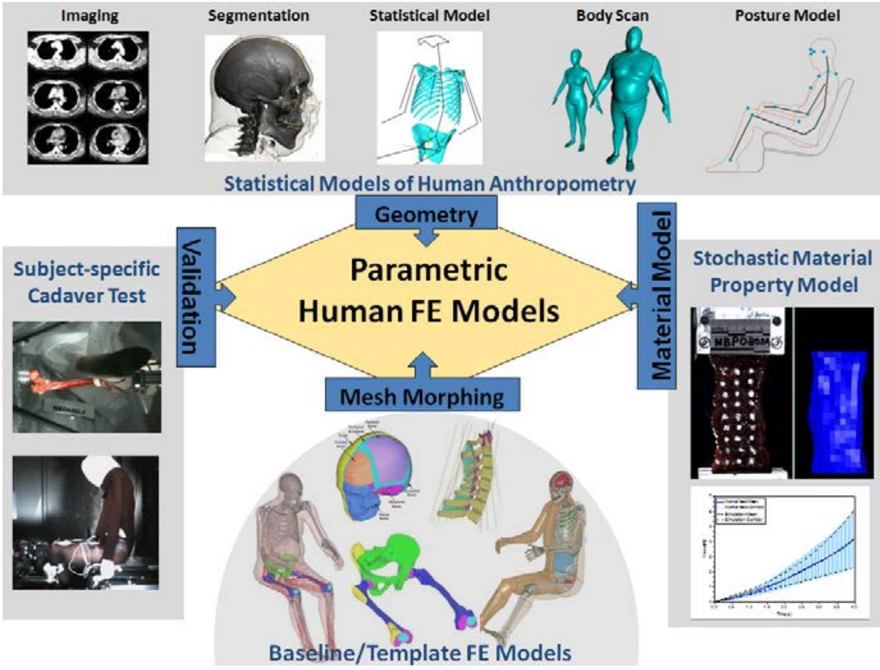

Figure 1: Overall technical schematic for developing a parametric human FE model

2.1. Statistical Human Body Geometry Model

UMTRI's human body geometry model combines statistical models of the cross-sectional geometry of the skeleton and soft tissue based on medical images (CT and MRI), seated external body contours based on whole-body laser scanning, and seated postures based on volunteer tests.

UMTRI has closely worked with the University of Michigan Health System using a protocol approved by an institutional review board to collect high resolution CT and MRI scans of humans. Once the CT/MRI images are available, several steps were then performed to extract the geometry data and develop statistical models that describe the geometry of various anatomic structures (Klein et al. 2015; Li et al. 2015b; Reed et al. 2009; Shi et al. 2014). The steps include CT image segmentation, landmark identification/template mesh fitting, registration, and development of statistical models of the extracted geometry using a combination of principal component analysis (PCA) and multivariate regression analysis. Mimics played an indispensable role in the process of developing the statistical geometry models, as CT images from hundreds of subjects (head CTs from 56 children, chest CTs from 89 subjects, femur CTs from 98 subjects, tibia CTs from 76 subject, and pelvis CTs from 116 subjects) were analyzed using Mimics in this study.

The principal component analysis (PCA) is used to express the geometry data on an orthogonal basis that can be more readily analyzed and to quantify the data variance in a more efficient way. Geometrically, the first principal component (PC) is the direction in the space of the data with the highest geometric variance, the second PC is in the direction orthogonal to the first PC with the second highest variance, and so on. Multivariate regression analysis is used to predict how the PC scores associated with the PCs generated by PCA vary with age, gender, height, body mass index (BMI), and/or other occupant parameters, and in turn predict detailed human body geometry. In addition, if a random component with standard deviation given by the residual vectors is added in the regression model, the possible variations of the human body geometry with the same set of subject parameters can be predicted.

The PCA method used here follows the method discussed by Li et al. (2011). The coordinates of the fitted template meshes or the landmarks were rigidly aligned using Procrustes alignment and rescaling (Slice 2007). Three coordinates at each of the nodes or the associated cortical bone thickness formed a geometry vector with a length of l (= total number of nodes x 3 for coordinates, or total number of nodes for thicknesses) denoted as **g** for one subject. The geometry vector for each subject was joined together to construct a geometry matrix $\mathbf{G}_1$. To make the PCA method work properly, the geometry matrix $\mathbf{G}_1$ was centered by subtracting the mean $\bar{\boldsymbol{g}}$ from each of the subject's $\mathbf{g}_i$. This matrix is called the data centered matrix **G**. PCA was computed by calculating the eigenvalues and eigenvectors of the covariance matrix of the centered geometry matrix **G**. **G** was decomposed as follows,

$$\boldsymbol{G} = \boldsymbol{SP} \qquad (1)$$

$$\boldsymbol{S} = \boldsymbol{GP^T} \qquad (2)$$

where **S** is an N x l matrix called principal component (PC) scores and **P** is the eigenvectors of **G**, which is an l x l-normalized matrix. Any subject's nodal coordinates or thicknesses could be obtained based on Equation 3,

$$\boldsymbol{g}_i^* = \bar{\boldsymbol{g}} + \boldsymbol{P}_N^T \boldsymbol{S}_{Ni}^T \qquad (3)$$

where $\mathbf{S}_{Ni}$ is the row of matrix $\mathbf{S}_N$ corresponding to the ith subject's PC scores.

To use the parameters such as age, BMI, and bone length to predict PC scores ($\mathbf{S}_k$), and in turn, to predict detailed LX geometry, a regression analysis was performed. A regression model was generated following the procedure used in Reed et al. (2009),

$$\boldsymbol{S}_k^T = \boldsymbol{CF} + \varepsilon^T \qquad (4)$$

where **F** is the feature matrix, **C** is the coefficient matrix, ε^T is a vector of zero mean and normally distributed residuals.

The whole body external contour scans were collected using a whole-body laser scanner Vitus XXL and a FaroArm 3D with Laser ScanArm. Landmarks on joint locations were also indentified. The same PCA and regression methods for the CT/MRI data processing were used for generating the statistical models of the human external body contour (Reed and Parkinson 2008). The skeleton/internal organ and external body contour geometries were then integrated together based on the corresponding landmarks identified in both models and the sitting posture model previously developed by UMTRI (Reed et al. 2002).

2.2. Mesh Morphing

Radial basis functions (RBFs) were used to morph the nodal locations of a baseline human FE model to target geometries specified by statistical shape and posture models. RBFs are widely used in image processing and neural networks (Bennink et al. 2007; Carr et al. 2001). In the present study, RBFs were used for 3D interpolation. Corresponding landmarks were identified on both the statistical geometry model and the baseline human FE model, so that nodal displacement at each landmark location can be calculated. Using RBFs, a 3D displacement field throughout the entire space of the human geometry is calculated based on the landmark displacements. By applying this displacement field to the baseline FE mesh, a new model with new geometry can be achieved. The basic formulas of the RBFs were provided below.

Given a set of distinct landmark points $\mathrm{X} = \{\mathrm{x_i}\}_{\mathrm{i=1}}^{\mathrm{n}} \subseteq \mathrm{R}^3$ and a set of function values $\{\mathrm{f_i}\}_{\mathrm{i=1}}^{\mathrm{n}} \subseteq \mathrm{R}$, requiring that interpretation function s(X) satisfies the conditions, $\mathrm{s(x_i)} = \mathrm{f_i}, \mathrm{i} = 1,2,3,\cdots,\mathrm{n}$
The function values $\mathrm{f_i}$ is determined by the data (coordinates and cortical bone thickness) on each pair of corresponding landmarks on the geometry model and the baseline FE model.

In order to obtain the smooth transformation, the following equation should be minimized,

$$\| s \|^2 = E(s) = \int_{R^3} [(\frac{\partial s(x)^2}{\partial x^2})^2 + (\frac{\partial s(x)^2}{\partial y^2})^2 + (\frac{\partial s(x)^2}{\partial z^2})^2 + 2(\frac{\partial s(x)^2}{\partial x \partial y}) + 2(\frac{\partial s(x)^2}{\partial x \partial z}) + 2(\frac{\partial s(x)^2}{\partial y \partial z})] d_x$$

In which $\|s\|^2$ is a measure of energy in the second derivation of s. The general solution of equation above is a function of the form,

$$s(x) = p(x) + \sum_{i-1}^{n} \lambda_i \varphi(| x - x_i |)$$

Where p is a low degree polynomial, λ_i is the weighting coefficient, φ is basic function, and $\|\cdot\|$ is Euclidean norm. The $s(x)$ needed to satisfy the orthogonality,

$$\sum_{i-1}^{n} \lambda_i = \sum_{i-1}^{n} \lambda_i x_i = \sum_{i-1}^{n} \lambda_i y_i = \sum_{i-1}^{n} \lambda_i z_i = 0$$

Combined interpolation and boundary conditions above, the RBF can be written in matrix form as,

$$\begin{pmatrix} A & P \\ P^T & 0 \end{pmatrix} \begin{pmatrix} \lambda \\ c \end{pmatrix} = \begin{pmatrix} f \\ 0 \end{pmatrix}$$

where $A_{i,j} = \varphi(|x_i - x_j|)$, $i, j = 1,2,3,\cdots,n$; $P_{i,j} = p_j(x_i)$, $i = 1,2,3,\cdots,n$, $j = 1,2,3,\cdots,l$.

Solving the linear system above can determine λ, c, and *s(X)*. Once the *s(X)* is determined, the nodal coordinates and associated cortical bone thickness for all the FE nodes from the new model can be calculated based on the information provided by the geometry model. Among various RBFs available, thin-plate spline function was oftern selected as the most suitable RBF for mesh morphing in terms of the geometry accuracy and mesh quality.

3. Results

3.1. Pediatric Head Model

A parametric pediatric head FE model was developed based on head CT scans from 56 children age 0-3 year-old (YO). The purpose of building this model is to quantify the growing/age effects on the head morphology as well as the resulting impact responses of a pediatric head. A total of 60 landmarks were identified on half of each child skull, with 28 on the skull surface and 32 along the suture. The 3D coordinates, skull thickness and/or suture width associated with each landmark were collected. PCA and regression analysis were conducted, so that the pediatric head geometry can be predicted by child age and head circumference. RBFs were used to morph a baseline 6-month-old child head FE model into models representing children at different ages. Figure 2 shows the process of developing the parametric model and examples of using RBF to morph the baseline model into 4 subject-specific head FE models. It was found that the RBF method can effectively change the baseline head model into a different geometry without reducing the FE mesh quality (Li et al. 2012). Since mesh morphing is an automated procedure, pediatric head models at any age from 0-3YO can be rapidly developed with the statistical pediatric skull geometry model and the RBF mesh morphing tool, which can provide valuable information on future investigation of age effects on pediatric head injuries. Details about the validation and application of this model can be found in studies by Li et al. (2011, 2013; 2015a; 2015b) and Hu et al. (2011b).

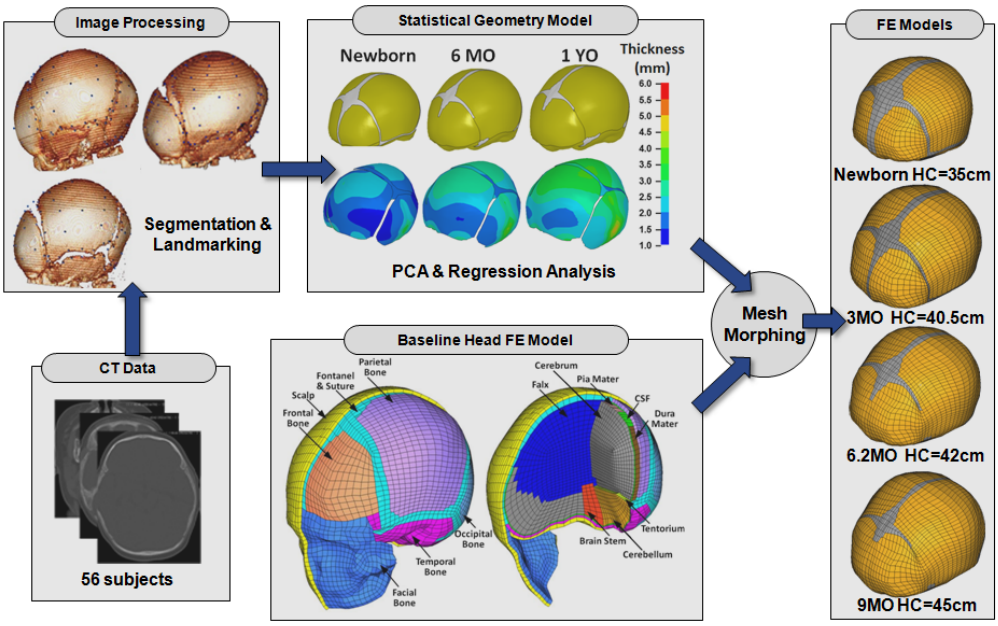

Figure 2: Subject-specific pediatric head FE model construction using mesh morphing method

3.2. Adult Ribcage Model

A parametric human ribcage FE model was developed based on CT scans from 89 subjects with ages between 18 to 89 years. On each rib, 32-44 landmarks were identified, and a total of 464 landmarks were used to quantify the morphology of half of the rib cage. PCA and regression analysis were performed, and a statistical model of the rib cage geometry that predicted rib cross-sectional geometry as a function of age, gender, height, and BMI was generated. RBFs were used to morph the rib cage model from the geometry of a template model (THUMS 4) to geometries representing combinations of occupant descriptors based on predictions of the PCA plus regression models.

Figure 3 shows the age, gender, stature, and body mass idenx (BMI) effects on ribcage geometry. Age affected rib angle and rib cage depth, with an increase in age raising the front edges of all ribs except for rib 11 and 12, which, in turn, resulted in greater rib cage depth overall. However, this rib cage depth increase was associated with a decrease in rib cage width, especially in the middle of the rib cage. The gender effect was significant in rib angle and rib cage depth, with men having flatter rib angle and greater rib cage depth than women with the same stature. Interestingly, in contrast to the age effects, men also sustained greater rib cage width than women with the same stature, indicating that men sustain greater rib cage volume compared with women with the same stature. In addition, the sex effect was consistent with different statures. The effects on rib cage geometry from an increase in BMI are very similar to those from an increase in age, both of which are associated with flatter rib angle, increase in rib cage depth and decrease in rib cage width. However, the BMI effects are larger than the age effects across the range in the current sample. Increases in stature increase the rib cage depth, width and height, but decrease rib angle. More detailed results can be found in the study by Shi et al. (2014).

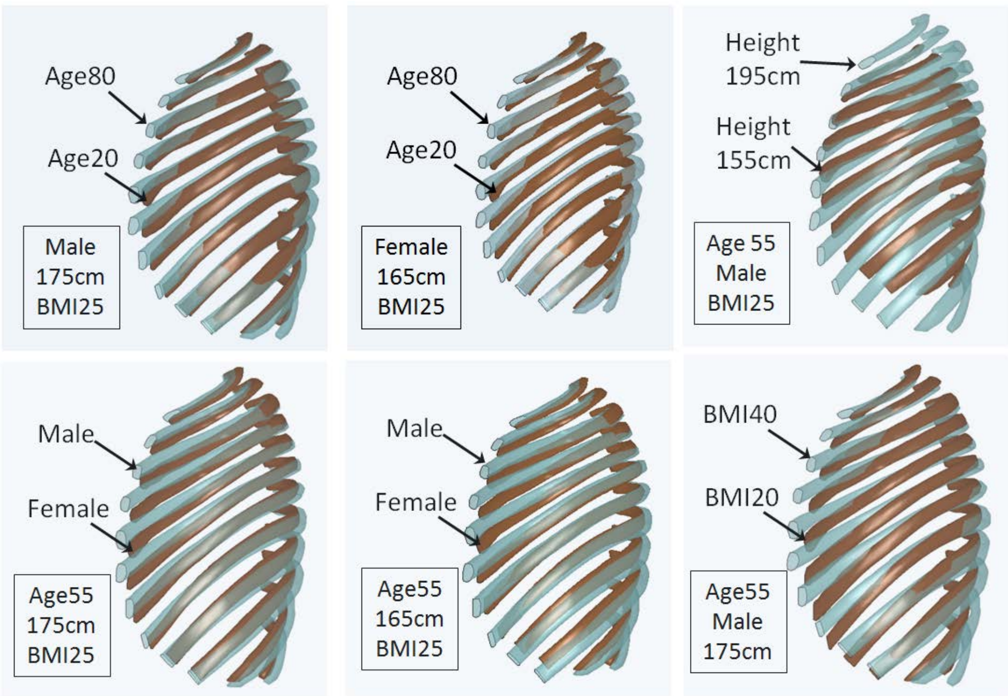

Figure 3: The effects of age, gender, stature, and BMI on rib cage geometries

3.3. Adult Lower Extremity Model

A parametric human lower extremity FE model (including femur, pelvis, and tibia) was developed based on CT scans from more than 100 subjects with ages between 17 and 89 years, heights 1.5-2m, and BMIs 15-46 kg/m^2. After PCA and regression analysis, the effects of age, femur length, BMI, and gender on femur geometry predicted by the femur parametric models are shown in Figure 4. These femur models were created by varying one parameter at a time and holding the other parameters constant. The cross-sections for five evenly spaced locations along the shaft are also shown for comparison. The models in these figures were aligned using a Procrustes approach rather than section centroids. Similarly, the effects of age, bispinous breadth, BMI, and gender on pelvis geometry predicted by the pelvis parametric models are shown in Figure 5.

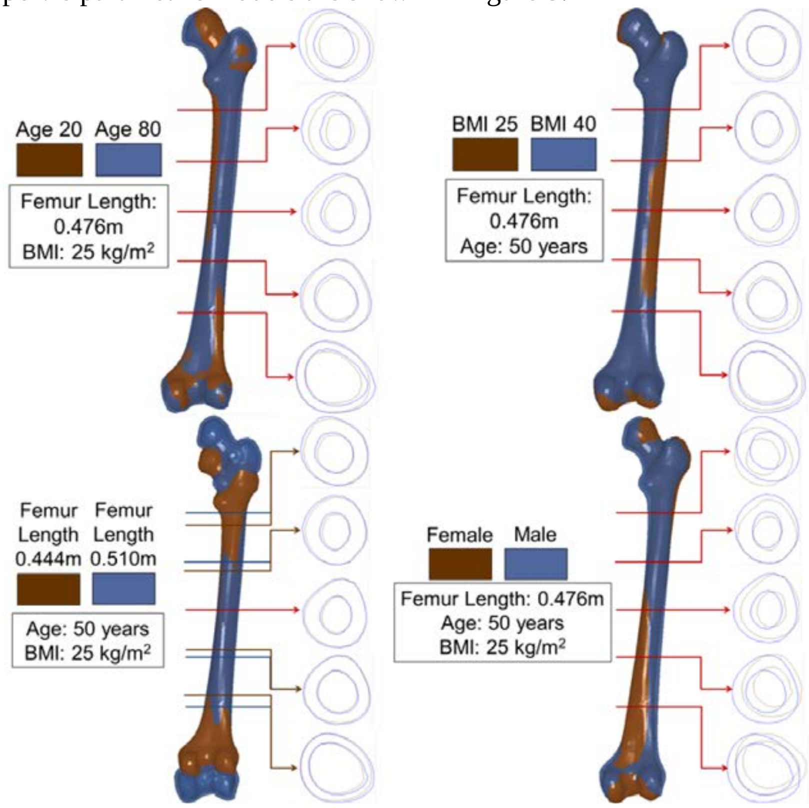

Figure 4: The effects of age, BMI, femur length, and gender on femur geometry predicted by the parametric models

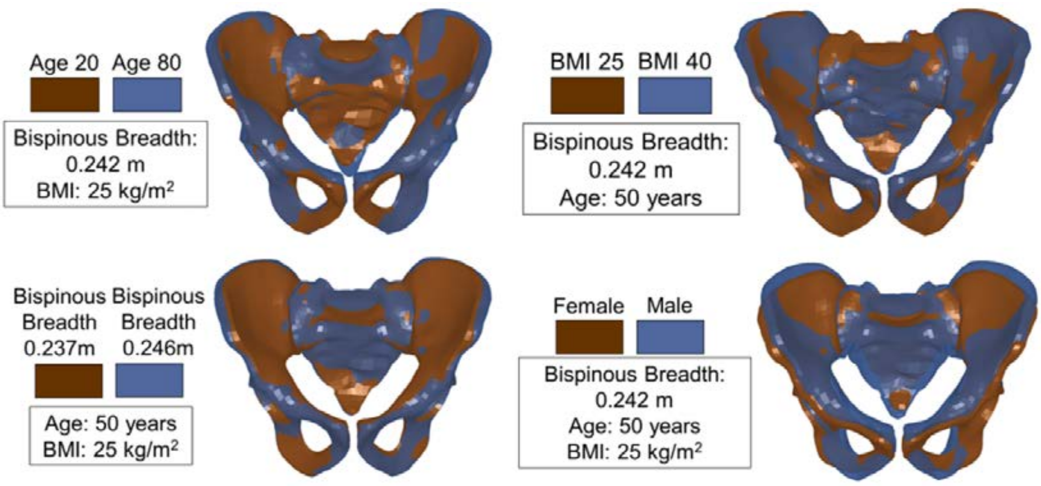

Figure 5: The effects of age, BMI, bispinous breadth, and gender on pelvis geometry predicted by the parametric models.

3.4. Obese Occupant Model

Obese occupant models were developed based on a combination of rib cage, lower extremity, and external body shape geometry models. Figure 5 shows the process of developing the obese human models. To combine the ribcage geometry model, lower extremity geometry model, and the external body contour model, these three models were co-registered using a baseline model as the reference. In this study, THUMS 4 50th percentile male model was used as the baseline model. This model contains approximately 630,000 nodes and 1.8 million elements. The impact responses of the THUMS 4 model have been validated for many body regions against cadaveric impact tests.

The statistical ribcage and lower extremity geometry models with a height of 1759 mm and different BMI values were first moved to the best corresponding locations and orientations matching the THUMS 4 model based on the hip, knee, and spinal joint locations. Then the same registration was conducted between the external body contour model and the THUMS 4 model. After these processes, the combined model including the ribcage, lower extremity, and external body contour was developed.

Several mesh morphing steps were involved in morphing the THUMS 4 into models with a different BMI. First, the ribcage geometry model was used as the target to morph the ribcage along with the abdominal wall of the baseline FE model. The ribcage surface and the abdominal wall were considered as the outer boundary of the internal organs and inner boundary of the subcutaneous tissue on the torso. Second, the external body contour model was used to morph the external torso surface of baseline FE model to define the outer boundary of the subcutaneous tissue. Finally, the internal organs and subcutaneous tissue of the baseline FE model were morphed according to the two boundaries defined above. Because BMI from 25 to 40 kg/m^2 caused only a small change on the ribcage geometry, the increase in size and mass was mainly due to the increased subcutaneous fat. The final morphed meshes for individuals with different BMIs are shown in Figure 6.

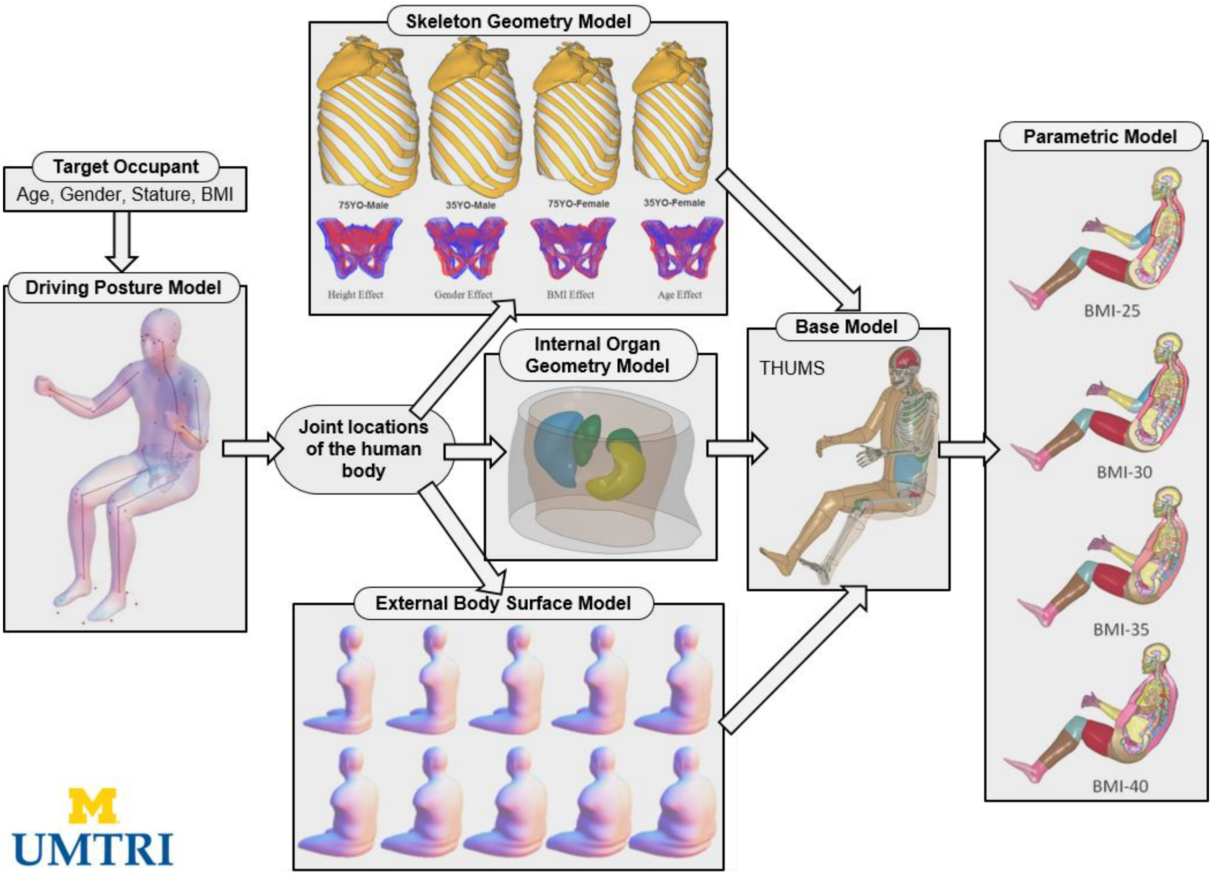

Figure 6: Morphing results from the baseline whole-body model to four targets with different BMI values

4. Conclusion

This paper summarized the UMTRI approach to developing human FE models that are parametric with occupant descriptors, including age, gender, stature, and BMI. Examples of how this approach was used to develop parametric FE models of the pediatric head, the adult ribcage, adult lower extremities, and whole-body adult models with different BMI values were presented. These results clearly demonstrated the feasiblity of this approach to develop parametric human models and the effects of human parameters on occupant geometry. The method presented in this study can enable future safety design optimizations targeting at various vulnerable populations that cannot be considered with current injury assessment tools.

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