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Focusing on Vulnerable Populations in Crashes: Recent Advances in Finite Element Human Models for Injury Biomechanics Research

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Abstract: Children, small female, elderly, and obese occupants are at greater risk of death and serious injuries in motor-vehicle crashes than the mid-size, young, male occupants. However, current injury assessment tools, including crash test dummies and finite element (FE) human models, generally do not account for different body shape and composition variations among the population. The opportunity to broaden crash protection encompassing all vehicle occupants lies in improved, parametric human FE models that represent a wide range of human attributes. In this study, a literature review demonstrates that recent studies on human anthropometry, finite element human modeling, mesh morphing, human tissue tests and whole-body cadaver tests have laid the groundwork for the new generation of human models. A framework for developing such models was proposed in this study. The developed models enable population-based simulations for future vehicle design optimizations targeting at various vulnerable populations that are not represented by current injury assessment tools.

Key words: motor-vehicle crashes; injury biomechanics; human model; vulnerable population; children; elderly; obesity

关注碰撞中易受伤害人群：用于损伤生物力学研究的有限元人体模型最新进展（英文）

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摘 要： 在汽车碰撞中，相对于平均身高的年轻男性，儿童、矮小女性、老人和肥胖者是易受伤害的人群，因而会有较高的死亡率和重伤率。但包括碰撞假人和人体有限元模型在内的现有伤害评价工具，一般未考虑人群中体型和身材组成的多样性。参数化人体有限元模型能够代表广泛人体属性，最大地拓宽碰撞安全所保护的人群。本综述发现：关于人体测量学、人体有限元模型、网格变换、人体材料试验和尸体试验的最新研究，为建立参数化人体有限元模型奠定了基础。本文提出了建立这样一个参数化的人体有限元模型的方案。该模型可模拟不同人群，对汽车进行安全优化设计，这是现有伤害评价工具所无法做到的。

关键词： 机动车碰撞；损伤生物力学；人体模型；易受伤害人群；儿童；老人；肥胖者

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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. Although most of those killed and injured are pedestrians and pedal cyclists, economic development is rapidly increasing the number of vehicle occupants who are at risk. Among the whole population, children, women, elderly, and obese populations are often at increased risk of death and serious injury compared with mid-size young men in motor-vehicle crashes (MVCs). Children are considered to be vulnerable for injuries because of their immature body structures; small women are vulnerable because of their body-sized related lower injury tolerance; the elderly are vulnerable because of aging-related morphological and physiological changes; and obese people are vulnerable because of their increased mass and body shape induced poor belt fit.

The current design process for vehicle safety systems relies heavily on crash tests to ensure design crashworthiness and occupant protection. Crash tests generally require the use of one or more crash dummies, known as anthropometric test devices (ATDs). The injury measurements from the dummy, such as the head injury criteria (HIC), chest deflection, and femur force, are compared with the injury thresholds developed based on human cadaver tests to assess injury risk. In the US, crash test programs include those defined in Federal Motor Vehicle Safety Standards (FMVSS), the US New Car Assessment Program (US-NCAP), and the safety rating system designed by Insurance Institute for Highway Safety (IIHS). In China, similar crash test programs include the CMVDR and China-NCAP. Unfortunately, all the current procedures for evaluating vehicle safety designs are mainly conducted using a few ATD sizes, generally representing midsize men (approximately 50th percentile by stature and body weight) and very small women (approximately 5th percentile by both stature and weight). Injury assessment tools that consider age and obesity effects, and capable of simulating the geometrical and biomechanical variations among the population that affect the ability to tolerate mechanical loading are not currently available. As a result, the ability of vehicle safety systems to effectively protect these vulnerable populations cannot be directly assessed.

The increased vulnerability of older, female, and obese occupants has been well documented in crash data. For example, field data analyses have shown that the effectiveness of vehicle airbag deployment on injuries is less for smaller occupants than mid-size men [1]. It was found that by Kent et al. [2] that if the injury risk for all ages were the same as that at age 20, 1.13-1.32 million fewer occupants would be injured each year in the US, which is nearly half of the total annual injury numbers in MVCs. Using similar field data, Zhu et al. [3] found that obese male drivers have a significantly increased risk for death due to MVCs compared with non-obese male drivers, especially at high speeds. All the above findings highlighted the potential benefit of safety systems specifically optimized for vulnerable populations.

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 [4], 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.

1 Increased Risks of Injuries for Different Vulnerable Populations in MVCs

To develop injury assessment tools for optimizing safety designs for vulnerable populations, it is necessary to understand injuries that these populations are most susceptible to and factors associated with their increased injury risks. Such knowledge is indeed complex by nature, but fortunately has been documented reasonably well in the literature.

Analyses of crash-injury databases demonstrate that occupant characteristics, including age, gender, and body mass index (BMI), a parameter measuring the obesity level, affect the injury risks for many body regions in MVCs. In particular, increased age in adults is associated with increased serious injury risks to almost every body-region in every crash mode. Among all the body regions, thoracic injuries are disproportionately common for occupants in older population [5-7], while lower extremity injuries are affected by age as well as gender and BMI [8, 9]. Similar findings were also reported by many other researchers [10-12], who found that obese individuals were more likely to have thorax and lower extremity injuries. Recently, Rupp and Flannagan [13] did a more comprehensive study by analyzing the age, gender, and BMI effects on injuries at different body regions as well as specific types of injuries. It was further confirmed that aging increases the risk of injury to every body-region, and the body regions for which the age effect is the most meaningful are the thorax and lower extremities in frontal crashes. Among all thorax and lower extremity injuries, the age effect is the most pronounced for the ribs and knee, thigh, and hip (KTH) complex. It was also mentioned that despite the large age effect, the effects of BMI and gender on thorax and lower extremity injuries are still important and should not be neglected when optimizing safety systems. Comparing with elderly, the obese and women, children are not always at increased risk of injury in MVCs mainly due to the help of child restraint systems. However, field data analyses show that children sustain different injury patterns than adults. In particular, children tend to have higher proportion of head and abdomen injuries than adults, likely because children have different sitting postures, kinematic responses and injury mechanisms due to shorter stature immature body structures.

2 Factors Associated with Increased Injury Risks for Different Vulnerable Populations

While being female, old, and/or obese all increase the risks of thorax and lower extremity injuries in MVCs, the exact mechanisms and factors associated with these increases are different. In general, factors affecting the risks of injuries can be grouped into three categories [14]: geometric characteristics, compositional characteristics, and material characteristics (Figure 1). Geometric characteristics include 3-D external body contour as well as size, shape, and orientation of the bones; compositional characteristics include the cross-sectional areas of the cortical bones and soft tissues; while material characteristics include the mechanical property of the cortical and cancellous bones as well as soft tissues.

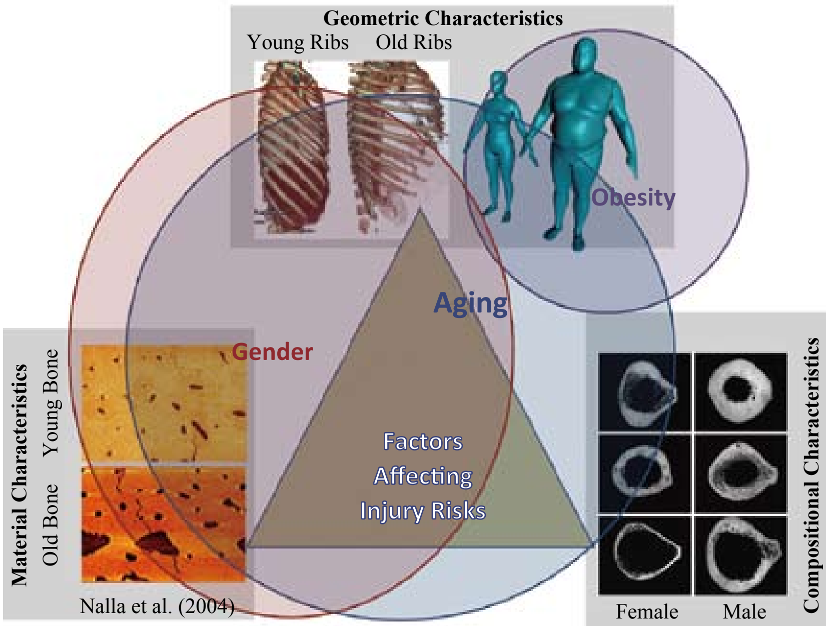


Fig. 1 Factors Affecting Injury Risks for Female, Older, and Obese Populations[15–16]

2.1 Aging Related Factors

It is well established that the injury tolerance decreases in thorax and lower extremities with aging [17-18], and such decrease is caused by the changes of factors in all three categories, i.e. geometric, compositional, and material characteristics. With aging, several geometric changes occur in the thorax region, including an increased kyphosis of the thoracic spine [19-20], and an increased rib cage depth due to more horizontally oriented rib angles in older population [14, 21]. These geometric changes may affect both the force required to deflect the thorax and the distribution of strain occurring within the thorax when a load is applied. Besides the geometric changes, compositional changes in cortical bone cross-sectional areas with aging also affect the injury tolerance significantly. For example, literature has shown that the cross-sectional area of a rib may decrease approximately 0.19 mm^2 per year after age 25 due to progressive circumendosteal resorption [22]. Likely, the cross-sectional area of cortical bone in an aged proximal femoral metaphysis also significantly influences its resistance to fracture [23-24]. In addition to geometric and compositional changes, both cortical and cancellous bones exhibit a decrease in Young's modulus with aging mainly due to the decrease in bone mineral density. The fracture toughness (failure strain/stress) of cortical bone also shows significant deterioration with aging [16].

2.2 Obesity Related Factors

Comparing to the aging effects, the obesity effects on injury risks in MVCs are relatively simple, with most effects coming from the adipose tissue related geometric changes. Field data analyses [10, 12], cadaver tests [25], and computational studies [26-27] have all shown that the increased mass can cause an obese individual to translate further forward in a frontal crash, thus increasing the contact loading and causing increased risks of thorax and KTH injuries. In addition, it was also found that obesity effectively introduces slack in the seat belt system by routing the belt further away from the skeleton, and the increased amount of adipose tissue around the pelvis/abdomen area will postpone the interaction between the lap belt and pelvis [28]. Consequently, the lower extremities of an obese occupant tend to move further forward in a frontal crash, causing increased risk of lower extremity injuries [26].

2.3 Gender Related Factors

Women generally have lower injury tolerance than men, but such gender effect is often complicated by its correlation with stature. Besides the stature effect, the gender difference can be reflected by both the geometric and material differences between male and female. For example, the differences in pelvic-bone anatomy and shape between genders could explain differences in the risk of some lower extremity injuries. A study [29] found that the female hip socket tends to face more forward and thereby engage a greater proportion of the surface area of the femoral head in a given posture during frontal-impact loading through the KTH complex than the male. This factor could decrease the hip fracture risk for female, but increase the possibility of a knee or thigh injury in frontal crashes. In addition, elderly women often have increased bone porosity and decreased bone mineral density and therefore a greater fracture risk than elderly men [30], although it is an interaction effect between age and gender.

Based on the above discussion, vulnerable populations may sustain higher injury risks due to the changes in geometric, compositional, and material characteristics. Injury assessment tools for optimizing safety designs for those populations have to incorporate these characteristic changes, so that their effects can be considered.

3 Current State-of-the-Art Tools for Injury Assessment

In the injury biomechanics literature, there are two major types of injury assessment tools available: ATDs and human computational models. Both of these tools have been developed to mimic human responses in injurious conditions. However, to become an accurate injury assessment tool, ATDs and computational models must be designed based on real human anthropometry and human mechanical response data under dynamic loading. Unfortunately, both the anthropometric data and mechanical response data for various populations, such as children, small female, elderly, and obese populations, are largely lacking, and the current development process for creating an ATD or a computational model is measured in years.

3.1 ATDs

ATDs have been widely used for years in evaluating safety designs for all types of vehicles. Currently, there are more than 20 commercial ATDs available representing children from age 0 to 10 and adults at three body sizes (large male, mid-size male, and small female) to mimic human impact responses at different crash modes (i.e. frontal, side, and rear impacts). However, adult ATDs were designed to represent young and healthy occupants, thus did not consider the aging or obesity effects. Data from impacts to post-mortem human subjects (PMHS), so called cadaver tests, are often considered as the gold standard for developing ATDs and the associated injury criteria [31]. Previous cadaver tests mainly focused on the average sized population, and almost always excluded PMHS who are obese or with osteoporosis, which is a common condition for older population. Previous cadaver tests have rarely included pediatric cadavers due to ethical concerns and the availability of specimens. Furthermore, PMHS tests are generally cost and time consuming, limiting the possibility of conducting a study with large number of sample size. Consequently most previous efforts to develop child ATDs and adult ATDs with different body sizes have involved scaling from mid-size adult data [32-33]. These scaled ATDs and their injury criteria assume that the body structures within the whole population are geometrically similar and cannot account for the detailed geometric, compositional, and material variations among the population. As a result, ATDs are substantially limited in their capability and accuracy for assessing injuries for vulnerable populations, such as the elderly, the obese, and children.

3.2 Finite Element (FE) Human Models

Table 1 lists recent available whole-body human FE models, including H-model [34], Ford Human Body Model [35-37], WSU Human Model [38-39], HUMOS2 [40-41], THUMS [42-43], and GHBMC model [44-45]. Except the Ford and WSU models, all other models are commercialized models, and the THUMS version 4 and the newly developed GHBMC model contain nearly 2 million elements, representing the state-of-the-art human models for injury prediction. However, even the THUMS 4 and GHBMC models have the same size and shape specifications and target responses as adult ATDs (i.e. the midsize male, small female, and large male) because of the time-consuming model development process and the desire to compare predictions between human FE models and ATD models. As a result, all the current FE human models are limited in the same way that adult ATDs are limited. These models are not able to capture the variability in body shape, age and gender with geometric, compositional, and material characteristics at a level that is sufficient to isolate their effects on injuries.

The HUMOS2 project developed one of the first existing parametric whole-body FE models. This model uses parametric anthropometry to scale a mid-size male FE model (Vezin and Verriest 2005) into different statures. However, the HUMOS2 is based only on a small number of whole-body skeletal landmark locations from mostly young, non-obese subjects and does not capture variability in the compositional and material levels. Furthermore, HUMOS2 models do not include variability in external body geometry, which is important to study when modeling obese occupants. More recently, a few studies have tried to turn the H-model and the Ford Human Body Model into models representing the aging population by changing the bone geometry and material properties [46-49]. However, these attempts are all limited within the mid-size male population, and also limited by the fact that only the overall shape of the ribcage and cortical bone thickness were varied without a systematic change on the cross-sectional geometry of each rib. Moreover, using the traditional approach to turn a human FE model of a young male into an older male is still time-consuming, which limited the number of models that can be generated for older population.

Table 1 An Overview of Recent Whole-Body Human FE Models for injury Prediction

First Author/Year	Haug 2004 Ito 2012	Ruan 2003 El-Jawahri 2010	Shah 2001 Kim 2005
Model Name	H-model	Ford Human Body Model	WSU Whole-body Human Model
Size	Mid-size male Small female	Mid-Size male	Mid-size male
Age	35, 75	35, 55, 75	No
Obesity	No	No	No
Posture	Seated	Seated	Seated
Figure (Most recent Version)			
Elements	Not stated	119,000	171,681

First Author/Year	Vezin 2005 Brunet 2006	Iwamoto 2002 Hayashi 2008	Gayzik 2011 Gayzik 2012
Model Name	Human Model for Safety 2 (HUMOS2)	Total Human Model for Safety (THUMS)	Global Human Body Models Consortium (GHBMC)
Size	Mid-size male Small female Large male scale to others	Mid-size male Small female Large male	Mid-size male
Age	No	No	No
Obesity	No	No	No
Posture	Seated	Seated and Standing	Seated
Figure (Most recent Version)			
Elements	Not stated	1.8 million	1.95 million

4 Parametric Human Finite Element Model

4.1 The Need for a New Parametric Human Finite Element Model

As indicated above, 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/or 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, 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 stature, age, gender, and BMI. However, such a model does not currently exist. The automated procedure for developing 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. Therefore, in this section, a literature review was conducted on recent development of technologies for building a parametric human FE model.

4.2 Method for Developing a Parametric Whole-body Human FE model

University of Michigan Transportation Research Institute (UMTRI) has developed a framework to build a parametric whole-body human FE model for crash simulations. A schematic of the UMTRI approach is shown in Figure 2.

The foundations of the parametric human model concept are statistical models of human geometry that describe morphological variations within the population as functions of occupant parameters (age, gender, height, 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, and these data are generally available in the literature. Since the parametric human FE model can be morphed into different subjects, subject-specific cadaver test reconstruction can be conducted for model validation. This will overcome the limitations of traditional method to validate human FE models, in which geometric and compositional differences generally exist between the cadaver and the human FE model.

4.2.1 Statistical Models of Human Anthropometry

To conduct an accurate FE analysis for injury assessment accounting for the size, age, gender, and obesity effects, a firm understanding of the population variability in both the 3-dimensional skeleton geometry and body surface contour is a necessity. The method to develop the statistical human body geometry model is illustrated in Figure 3. At the core of this method are three models, including the sitting posture model, body surface contour model and bone geometry model. The posture model, such as that reported by Reed et al. [50], can predict the locations of skeletal/joint landmarks that describe the orientations of body segments as functions of occupant characteristics. These skeletal/joint landmark locations and associated occupant characteristics also serve as inputs to the body surface contour model and the bone geometry model. The combined outputs of these statistical models are a few thousand points that define body posture, the size and shape of the body external surface, and skeleton (skull, ribcage, lower extremity, etc) geometries associated with a particular set of occupant characteristics.

In the literature, several studies have characterized the age effects in the kyphosis of the thoracic spine [17-18], as well as the rib cage depth and rib angles in younger and older populations [14]. However, in these early studies, only simple

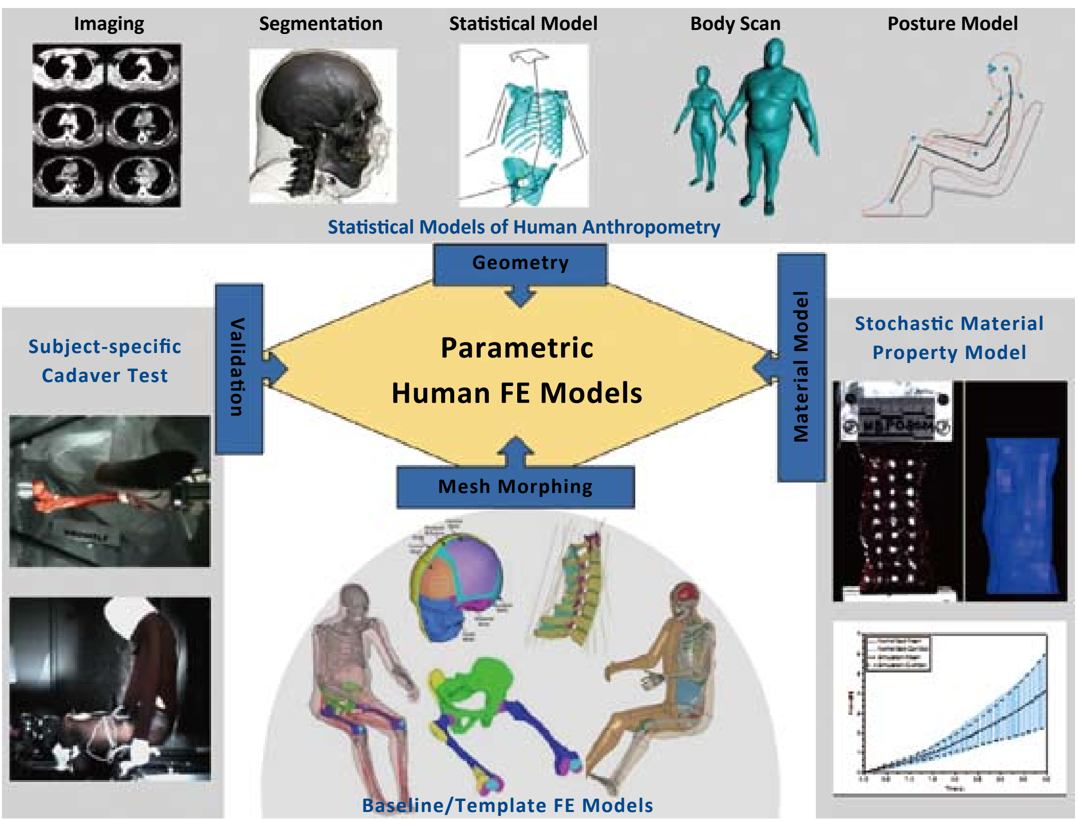


Fig. 2 Overall Technical Schematic for Developing a Parametric Whole–Body Human FE Model

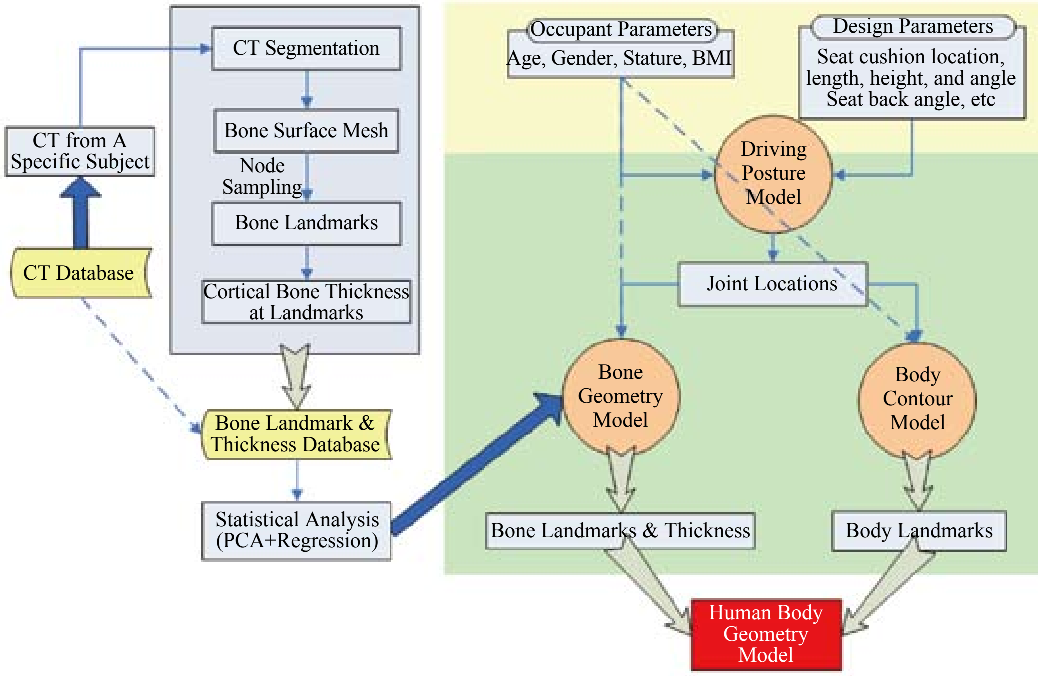


Fig. 3 Method for Developing the Statistical Human Body Geometry Model

anthropometric data were measured, which did not include 3-D geometrical information of the thorax. More recently, Gayzik et al. [19] quantified age-related shape change of male thorax using CT image analyses and Procrustes superimposition method based on 106 landmarks on the rib cage. Multivariate linear regression was also used to determine the relationship between landmark locations and age. It was found that age significantly affects the ribcage shape. The statistical model of human ribcage developed in this study is valuable for developing age-related parametric human thorax FE model. However, the geometry model did not represent the detailed 3-D cross-sectional geometry of the bones, nor cortical bone thickness.

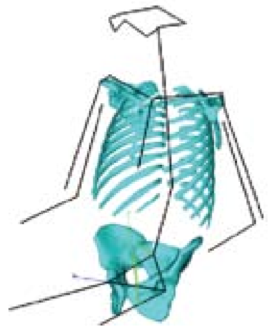
Reed et al. [51] developed a method to build statistical models of human skeletal geometry based on radiological images. The steps include CT image segmentation, landmark identification, registration, and development of statistical models of the extracted geometry using a combination of principal component analysis (PCA) and multivariate regression analysis. PCA was 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 was used to predict how the PC scores associated with the PCs generated by PCA vary with occupant parameters, such as age, gender, height, and body mass index (BMI), 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 method developed in this study built a foundation of developing statistical human geometry models based on various datasets, including medical images and body scans.

The methods proposed in Reed's study have been applied in several studies within his research group [51-53]. Figure 4(a) shows the average geometry of pelvis, thorax, and scapula for 10YO children using statistical analysis of CT images from more than 100 5-12 YO children [51], while Figure 4(b) shows the male torso surface shape with the same height but different body mass index (BMI) values using the PCA+Regression method [53].

In a more recent study by Klein et al. [54], the height, gender, BMI, and age effects on the bone geometries of lower extremities were quantified used the PCA+Regression method and is shown in Figure 5, in which geometries in blue represent male or maximum height, BMI or age, while geometries in red represent the opposite. Occupant height was the only significant predictor of tibia geometry; height, gender and BMI were significant predictors of femur geometry; and height, gender, BMI, and age all significantly affected pelvis geometry. These findings provided valuable information for quantifying occupant parameter effects on their impact responses.

4.2.2 Mesh Morphing

As mentioned earlier, due to the time-consuming process for building a human FE model, current whole-body human



(a) Pelvis, thorax, and scapula geometry for a typical 10YO child [51]

(b) Male torso surface shape with fixed height of 1755mm and BMI from 18 to 45 [53]

Fig. 4 Previous Studies Using PCA+Regression Method to Develop Human Geometry Models

FE models are only in a few body sizes, thus are not able to capture the variability in geometric, compositional, and material characteristics at a level that is sufficient to isolate stature, gender, age, and BMI effects on injuries.

Although there is large variability in human body geometry, we should also recognize that human bodies are all anatomically similar. It is possible that the FE mesh from a human FE model can be changed smoothly into other geometries without developing new FE meshes. Therefore, the basic concept for developing a parametric human FE model is to morph a baseline model into different geometries using automated mesh morphing method. In this way, multiple models with different combination of human characteristics can be generated rapidly, which will enable large-scale design optimization considering population variability.

In the literature, although mesh morphing method was introduced in late 90 s, parametric FE modeling concept only became popular in very recent years. Table 2 lists some of the studies on developing parametric human FE models. All these models are at the component level, and a parametric whole-body human FE model is not yet available. Although the mesh morphing methods varied significantly among different studies, they can be divided into two types: landmark-based mesh morphing or surface-matching-based mesh morphing. Relatively speaking, landmark-based mesh morphing is more suitable for linking the statistical geometry model to the baseline FE model, because the nature of the statistical geometry model is also landmark-based.

Among landmark-based mesh morphing methods, radial basis functions (RBFs) are the most popular. RBFs have been widely used in image processing and neural networks [55-56]. To use RBFs for mesh morphing, corresponding landmarks need to be 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 3-D displacement field throughout the entire space of the human geometry can be 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. Among various RBFs available, the thin-plate spline function and multiquadratic function are the most suitable RBFs for mesh morphing in terms of the geometry accuracy and mesh quality based on a study by Li et al. [57]. It should be noted that RBFs can not only morph the FE mesh, but also

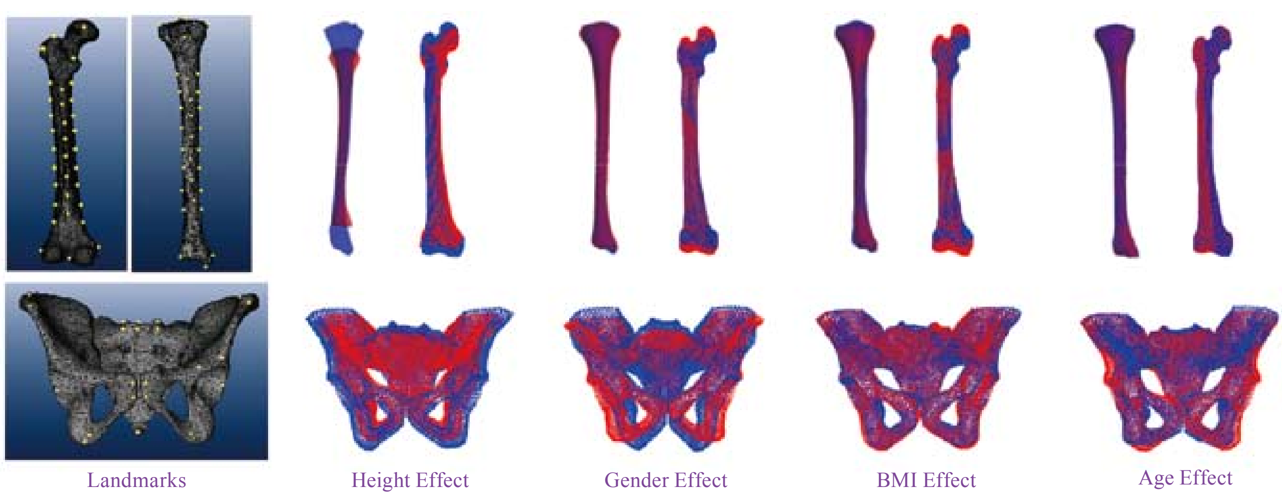
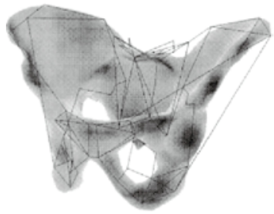
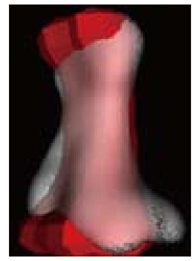
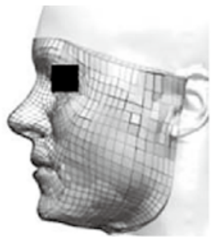
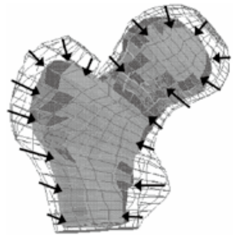
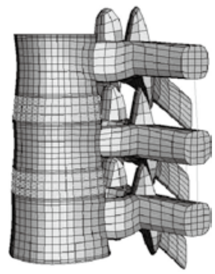
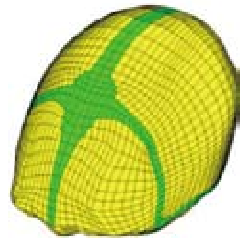


Fig. 5 Lower Extremity Landmarks and Human Parameter Effects on Bone Geometries

Table 2 An Overview of Recent Parametric Human FE Models

Figure				
Body region	Pelvis	Femur	Femur	Phalanx bone
Morphing method	Kriging	Surface matching and Laplace smoothing	Radial basis function	Deformable registration algorithm
Morphing type	Landmark-based	Surface-matching	Landmark-based	Surface-matching
Reference	Besnault (1998) [58]	Bryan [59]	Grassi [60]	Grosland [61]
Figure				
Body region	Face	Femur	Spine	Head
Morphing method	Mesh-Matching algorithm	Elastic volumetric registration	Landmark-based parametric meshing	Radial basis function
Morphing type	Surface-matching	Surface-matching	Landmark-based	Landmark-based
Reference	Bucki [62]	Couteau [63]	O'Reilly [64]	Li [52]

systematically change the information associated with each node, such as the cortical bone thickness values and material properties.

The basic formulas of the RBFs were provided below.

Given a set of distinct landmark points $X=\{x_i\}_{i=1}^{n} \subseteq R^3$ and a set of function values $\{f_i\}_{i=1}^{n} \subseteq R$, requiring that interpretation function $s(X)$ satisfies the conditions,

$$s(X_i)=f_i,\ i=1, 2, 3, \cdots, n. \quad (1)$$

The function values 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,

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

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,

$$s(x) = p(x) + \sum_{i-1}^{n} \lambda_i \varphi(| x - x_i |)\,. \quad (3)$$

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,

$$\sum_{i-1}^{n} \lambda_i = \sum_{i-1}^{n} \lambda_i x_i = \sum_{i-1}^{n} \lambda_i y_i = \sum_{i-1}^{n} \lambda_i z_i = 0\,. \quad (4)$$

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

$$\begin{pmatrix} A & P \\ P^T & 0 \end{pmatrix}\begin{pmatrix} \lambda \\ c \end{pmatrix} = \begin{pmatrix} f \\ 0 \end{pmatrix}. \quad (5),$$

where $A_{i,j} = (|x_i - x_j|)$, $\quad i, j = 1, 2, 3, \cdots, n$;

$$P_{i,j} = P_j(x_i), \quad i = 1, 2, 3, \cdots, n, \quad j = 1, 2, 3, \cdots, l.$$

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.

A specific example of using RBFs to develop a parametric child head FE model [52, 65] is shown in Figure 6.

It was found that the RBF method can effectively change the baseline head model into a different geometry without reducing the FE mesh quality. The whole-body human structure is certainly more complicated than the head alone, but previous studies have shown great potential of using RBFs to develop a parametric whole-body human FE model.

4.2.3 Human Tissue Material Properties for A Parametric Human Model

Once the FE mesh is generated, material properties suitable for occupants with different characteristics, such as age, gender, and BMI, need to be assigned to different body components. The aging and gender effects on bone material properties have been widely reported in the literature [66-72], but similar effects on soft tissue material properties are not well understood. Furthermore, large variations generally exist in material properties of human tissues even in the population with the same age and gender. As a result, stochastic material models, including not only the means but also the standard deviations of the material parameters, are needed for a parametric whole-body human model. Such models are available for human tissues at different body regions, but the method of developing such models has been developed and demonstrated by a study by Hu et al. [73], in which a stochastic visco-hyperelastic model of human placenta tissue was developed using a combination of tensile testing, specimen-specific FE modeling, and stochastic optimization methods.

4.2.4 Parametric Human Model Validation

Although cadaver tests have been routinely used to validate human FE models, the validation was always limited to mid-size male and small-female models. Aging and obesity effects have never been considered in the model validation process. The major difference between validating a single human FE model and a parametric human FE model is that the parametric model can be morphed into geometries representing specific cadavers. Consequently, more accurate subject-specific model validation can be conducted by the parametric human FE model, which would lead to better understanding of the relationship between material properties and human impact responses.

The validation of a parametric human FE model should involve morphing the parametric model to represent groups of individual cadavers and morphing segments of the model to represent cadaver bone specimens used in biomechanical tests to characterize human body response and tolerance, reconstructing the loading conditions that were applied to each of these subjects/specimens, and comparing predicted responses to experimentally measured responses for different test subjects. The goal of this validation process is to match the overall trends in measured responses for each group of test subjects considering the aging and obesity effects rather than only matching single response cases.

Table 3 lists some studies that can be used for model validation specifically focusing on the aging and obesity effects.

It is clear that cadaver studies with whole-body CT scans, which are the most suitable for parametric model validation, are still largely lacking. For cadaver component tests with CT scans available, subject-specific FE models should be generated as part of the test reconstruction process, while for whole-body cadaver tests, the subject-specific FE model should be generated to not only represent accurate geometry of the skeleton and body shape but also the sitting posture of the cadaver in the test. During the model validation process, material properties and boundary conditions can be tuned using optimization methods so that model responses best fit the cadaver responses. Comparing to the traditional human model validation method, in which the responses of a single human model are compared with a testing corridor without considering the geometry variations among the cadavers, subject-specific model would significantly reduce the geometry and posture differences between the model and the cadaver. Consequently, the material properties of the model can be tuned more accurately, and the errors in the final impact responses can be reduced significantly. However, it should be

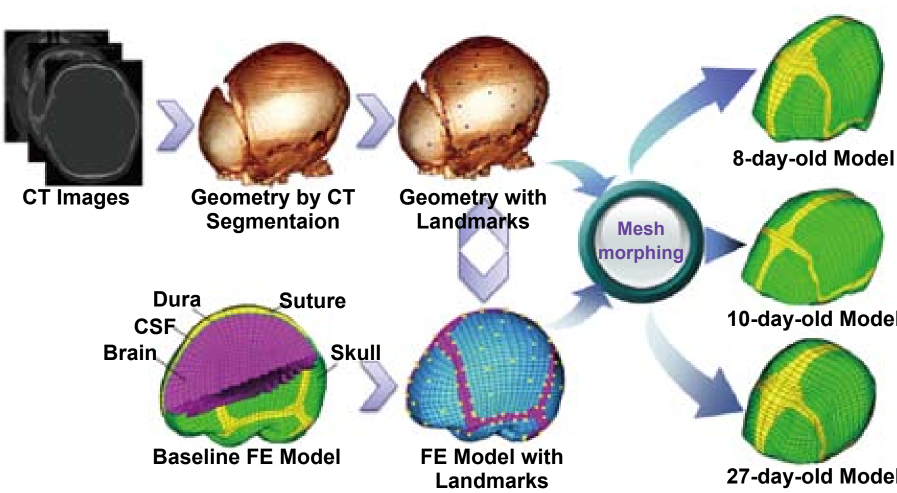


Fig. 6 Pediatric Head FE Model Construction Using Mesh Morphing Method [52, 65]

Table 3 Studies can be Used in Validating the Parametric Human FE Model

Study	Ref.	Validation Data	Body Region	Effects	CT Available
Ivarsson, et al.	[74]	Femur compression/bending	Femur	Aging	Yes
Rupp, et al.	[75]	Pelvis, femur	Femur, Pelvis	Aging	No
Rupp, et al.	[76]	Knee impact response	KTH	Aging	No
Charpail, et al.	[77]	Rib bending	Ribs	Aging	Yes
Vezin, et al.	[78]	Isolated rib cage impact	Rib cage	Aging	No
Kroell, et al.	[79]	Thorax pendulum impact	Thorax	Aging	No
Kent, et al.	[80]	Various thorax impact conditions	Thorax	Aging	No
Kent, et al.	[25]	Whole body sled test	Whole body	Obesity	No
Foster, et al.	[81]	Abdomen belt loading	Abdomen	Obesity	No
Lamielle, et al.	[82]	Abdomen belt loading	Abdomen	Obesity	No

noted that to achieve the goal of parametric model validation, additional cadaveric studies with whole-body CT scans focusing on aging, gender, and obesity effects, are necessary.

5 Conclusions

In this study, a literature review was conducted on the age, gender, and obesity effects on MVC-induced injuries and recent development of human modeling technologies for investigating the impact responses for various vulnerable populations. It was found that recent studies on human anthropometry, FE human modeling, mesh morphing, human tissue tests and whole-body cadaver tests all converge nicely toward a parametric human finite element model which can represent a wide range of human attributes. A framework was also proposed to develop such a model, which will enable population-based simulations for future vehicle design optimizations targeting at various vulnerable populations that cannot be represented with current injury assessment tools.

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