Comparison of Boundary Manikin Generation Methods

M. P. REED and B-K. D. PARK

* University of Michigan Transportation Research Institute

Abstract

Ergonomic assessments using human figure models are frequently conducted using a small family of manikins chosen to span a large percentage of target user population with respect to anthropometric variables. Boundary manikins have most frequently been generated through a process that uses a principal component analysis of selected standard anthropometric variables to establish target dimensions that are subsequently used to scale a figure model. The availability of three-dimensional body shape data and associated statistical methods provides some alternatives. In particular, the principal component analysis can be conducted on the vertices that define the body size and shape and boundary manikins can be selected in that space. This paper compares two methods of generating manikin and provides some guidance on both manikin generation and application.

Keywords: body scanning, body shape modeling, boundary manikins

1. Introduction

For many ergonomic analyses, the distribution of body size among the target user population is an important consideration. Scaling of figures in digital human modeling software systems to represent people with a range of sizes is considered a baseline capability and considerable effort has been focused on developing and evaluating this functionality.

Ideally, virtual ergonomic assessments would be conducted with thousands of avatars representing the target user population, each possessed of not only appropriate body dimensions but also strength, range of motion, skills, and preferences. However, with current software systems and procedures, only body size and shape is typically varied, although range of motion and strength capability are also parameterized. Importantly, efficiently evaluating a candidate design with thousands of virtual users is currently beyond the capability of most systems. The question then arises as to which small number of manikins should be used for the analysis.

Many design decisions are made “in the tails” of the anthropometric distributions, i.e., a particular design feature might disaccommodate people who are either large and small on some dimension. Hence, manikins are commonly chosen on the “boundary” of some anthropometric space so that the family of manikins to be used includes individuals who are large and small on various dimensions.

A variety of methods have been proposed for selecting boundary manikins. Often manikins are chosen based on univariate percentiles on one or two dimensions, such as 5th-percentile stature and body weight. It is immediately apparent that such manikins do not provide meaningful accommodation estimates, because stature and body weight are rarely limiting dimensions.

Recognizing that most ergonomic analyses involve multiple dimensions, researchers and practitioners have employed a range of multivariate methods. A set of standard anthropometric variables are chosen that are related to particular analysis or, more commonly, a variety of possible analyses. Values for these variables are obtained from a population assumed to be representative of the target user population. A multivariate statistical analysis is then conducted to determine “cases”, i.e., vectors of anthropometric variables, that lie relatively far from the center of the distribution. The most common statistical method is principal component analysis (PCA), which identifies the eigenvectors and eigenvalues of either the covariance or correlation matrix of the anthropometric variables for the selected population. This is usually performed separately for men and women.

PCA performs a rotation of the data into a new space (coordinate system) such that each axis (eigenvector or principal component -- PC) is orthogonal to every other and the values of the observations on these axes are uncorrelated. By convention, the first PC is oriented in the direction

*Corresponding author. Email: mreed@umich.edu

that the data have the highest variance, the second PC is the orthogonal direction with the next highest variance, and so on. Thus, the first few PCs may capture most of the variance in a dataset, depending on how correlated the variables are.

For large numbers of observations, the distribution of the data in the PC space becomes approximately multivariate normal. As a consequence, parametric methods for establishing a volume within which a desired percentage of the population lies (under the multivariate normal assumption) are attractive. Most commonly, an ellipsoid assumed to contain 95% of the single-sex population is constructed and boundary manikins are defined on the surface of the ellipse. Although the method can be applied at any dimension up to the number of variables in the anthropometric dataset, conventionally manikins have been generated in the space defined by the first 3 PCs. Selecting manikins where the axis intercept the ellipse generates 6 manikins. An infinite variety of other manikins can be generated on the ellipse surface. Choosing midpoints between axes gives an additional 8 manikins for a total of 14 each sex.

Given that the space of the male and female manikins intersects, those female manikins lying within the male space are sometimes deleted along with male manikins lying within the female space (Guan et al. 2012). At the conclusion of this step, these "manikins" are vectors of standard anthropometric variables. For human figure model analysis, they must be turned into 3D software manikins. Each software provider has a different methodology for scaling their figure given standard anthropometric inputs. Some problems are immediately apparent. First, the list of variables used in the PCA may not match the list of variables required for scaling the figure. Second, the method for scaling the figure may not result in realistic manikins because other variables not specified may not be set appropriately.

An alternative approach to generating body shapes as a function of standard anthropometric variables has been available for some time (Allen et al. 2004) The locations of mesh vertices defining the body surface are predicted using statistical regression using data from body scan studies. Typically, a PCA is first conducted to obtain a reduced-dimension representation of the body shape space prior to regression. However, these methods are not yet widely used in commercial human modeling software.

The process described above begins with a fairly small number of standard anthropometric dimensions (lengths, breadths, circumferences) and ends with a 3D manikin. The availability of high-fidelity whole-body scan data provides an opportunity to generate boundary manikins directly. Using PCA, the process proceeds in the same manner as with the standard approach, except that the PCA is conducted on the vertices of a polygonal mesh defining the body surface. In this manner, the analysis considers a large number of body features simultaneously, rather than only a few selected dimensions.

This paper compares manikins generated using these alternatives and discusses the implications for ergonomics evaluation. The contexts in which one approach would be preferred are also discussed.

2. Materials and Methods

2.1. Data Source

The current analysis was conducted using data from 236 U.S. Army Soldiers gathered as part of the Seated Soldier Study (Reed and Ebert 2013). Standard anthropometric measures were also obtained and each participant was scanned minimally clad using a VITUS XXL laser scanner in a standing posture. The scan data were fit using a homologous template mesh and procedures published previously (Park and Reed 2015). The template produces a watertight mesh with 14427 vertices and 14454 polygons. Following fitting, the meshes were made symmetrical by averaging left and right vertices. Pose correction to achieve consistent upper-extremity angles was conducted using a morphing method based on radial basis functionss.

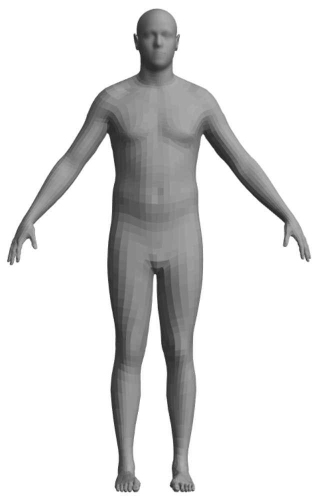

Figure 1. Mean figure.

2.2 Anthropometry PCA Boundary Manikins (A-PCA-BM)

The anthropometry PC was conducted using the variables listed in Table 1. These variables were selected in previous work (Reed et al. 2014) as a minimal set able to represent the primary aspects of anthropometric variation. The PCA was conducted using the covariance matrix. The first 3 PCs accounted for 95.5% of the variance. Boundary manikins were computed on the surface of an ellipsoid on the first 3 PCs enclosing 95% of the distribution under the multivariate normal assumption. In addition to the 6 manikins defined by the intersection between the axes and the ellipsoid surface, 8 additional manikins were defined at {±1, ±1, ±1} in the normalized space.

Table 1
Body Dimensions Used for PCA On Standard Anthropometry (A-PCA)

Stature	BMI†
Biacromial Breadth	Knee Height, Sitting
Chest Circumference	Waist Circumference
SH/S*	Hip Circumference
Head Circumference	

† Body mass index, kg/m^2
* Ratio of erect sitting height to stature

To obtain 3D manikins, the anthropometry vectors were input to a regression model predicting PC scores as a function of anthropometric variables. The resulting scores were used to generating manikins, using all PCs.

2.3 Body Shape PCA Boundary Manikins (BS-PCA-BM)

The PCA on the body shape data was conducted using a geometry vector that included standard anthropometric variables, the coordinates of 96 body landmarks, and the coordinates of the vertices of the template mesh. Manikins generated in the space defined by the first 3 principal components, which accounted for 85% of the variance. Because the standard anthropometric variables were included in the geometry vector used for PCA, the associated body dimensions could be obtained.

3. Results

A-PCA-BM

Table 2 lists summary statistics for the anthropometry vectors (all BMs are listed in the appendix). For each variable, the minimum and maximum are presented, since the typical boundary manikin analysis assesses all manikins against a design. The percentiles of the associated minimum and maximum values relative to the original dataset are also presented.

Several trends that reveal functional aspects of the A-PCA-BM procedure are apparent in the percentile values. As expected, the percentiles for individual variables are extreme, with the minimum BM values for 6 variables smaller than any individual in the dataset. The upper tail values are between the 90th and 99th percentiles. The range of percentiles is smallest for SH/S due to the relatively small range of this variable. This illustrates that the scale of a variable, and the number of other selected variables with which it is correlated, strongly influence the outcome of the PCA. BMI and chest, waist, and hip circumference are well correlated and represent four of the nine variables, and hence have similar (and extreme) percentile values. In contrast, the percentile range for SH/S and biacromial breadth are smaller. Table 2 reinforces the fact that BMs generated using the A-PCA method will have unpredictably extreme values, depending on the particular variables included in the analysis.

Table 2
Summary Statistics for A-PCA-BM

Manikin	Min	Max	Min%	Max%
Stature	1576	1932	0.0%	98.7%
BMI	16.8	37.0	0.0%	98.3%
SH/S	0.505	0.541	11.4%	89.8%
Biacromial Breadth	378	436	5.5%	94.5%
Knee Height, Sitting	485	626	0.0%	97.9%
Head Circ	553	589	9.3%	90.3%
Chest Circ	811	1272	0.0%	98.3%
Waist Circ	619	1206	0.0%	98.3%
Hip Circ	841	1249	0.0%	98.7%

BS-PCA-BM

For comparison, Table 3 shows statistics for the standard anthropometric variables obtained using the BS method. As expected, the values differ from those obtained using the A-PCA method. The range of stature values is similarly extreme, and the range for SH/S is very similar. For the other variables, the range of body dimensions is generally less extreme. This is expected, because in general variables not closely related to the first 3 PCs will not vary widely in the resulting BMs. BMI, in particular, spanned only the central 50% of the population in this analysis.

Table 3
Summary Statistics for BS-PCA-BM*

Manikin	Min	Max	Min%	Max%
Stature	1570	1938	0.0%	98.7%
BMI	24.0	29.8	25.4%	78.8%
SH/S	0.506	0.541	11.9%	89.8%
Biacromial Breadth	387	427	11.4%	86.4%
Knee Height, Sitting	482	629	0.0%	98.3%
Head Circ	556	586	14.4%	84.7%
Chest Circ	966	1116	17.8%	81.8%
Waist Circ	826	1000	23.3%	80.5%
Hip Circ	964	1126	12.7%	86.9%

* Based on reconstructions from the PC score vector generated from the BM-generation procedure.

Figures 2 and 3 show the manikins generated using the two techniques, sorted by stature. As suggested by Tables 2 and 3, the manikins span a similar range of stature, but the range of circumferences and BMI is larger in the set of manikins generated by standard anthropometry.

4. Discussion

With current human modeling software, the ideal of conducting ergonomics analysis with thousands of manikins representing the user population is generally not feasible, so analyses must be conducted with smaller numbers of carefully chosen manikins. The outcomes from the widely-used A-PCA-BM approach are strongly dependent on the choice of input variables. For example, choosing multiple variables correlated with body weight will result in less extreme values for length dimensions in the resulting manikin families. This may be seen as a strength of the method, in that dimensions can be chosen that are closely related to the application. In practice, though, not all of the selected anthropometric variables will be equally important and most assessments will be single-tailed, i.e., only affected by large or small body dimensions and not both.

In the current study, BMs generated using a set of standard anthropometric data and rendered in 3D using a statistical body shape model showed a wider range of BMI and segment circumferences than BMs generated in the first 3 PCs of the body shape space. In both cases, manikins with a wide range of stature and a comparable range of SH/S were generated.

An advantage of the BS-PCA-BM method is that no decisions are needed with respect to the variables to be included. However, the choice of the number of manikins to select and where they are to be located in the body shape space is arbitrary. For consistency with typical practice, both the A-PCA and BS-PCA manikins were selected in the space of the first 3 PCs, but other approaches are possible. For example, BMs could be selected on the surface of a hyperellipsoid in 5-dimensional space, then culled based on whether they represented boundary cases on any variables of interest.

Most importantly, neither method is “correct”. In addition to being dependent on the underlying database, accommodating the manikin families generated by these techniques does not guarantee any particular level of accommodation. Because PCA-BMs tend to be extreme, designing to accommodate all of a family of BMs may be unnecessarily limiting.

5. Conclusion

PCA-BMs can be generated in a body shape space rather than using standard anthropometry. This eliminates the need to select a set of body dimensions of interest a priori, but may produce a set of BMs that are less extreme. Care must be taken in interpreting the results of a BM analysis because the selection of manikins is essentially arbitrary, because no principled reason exists to prefer one method of generation over another, and analyses with BMs do not produce any particular level of accommodation in designs.

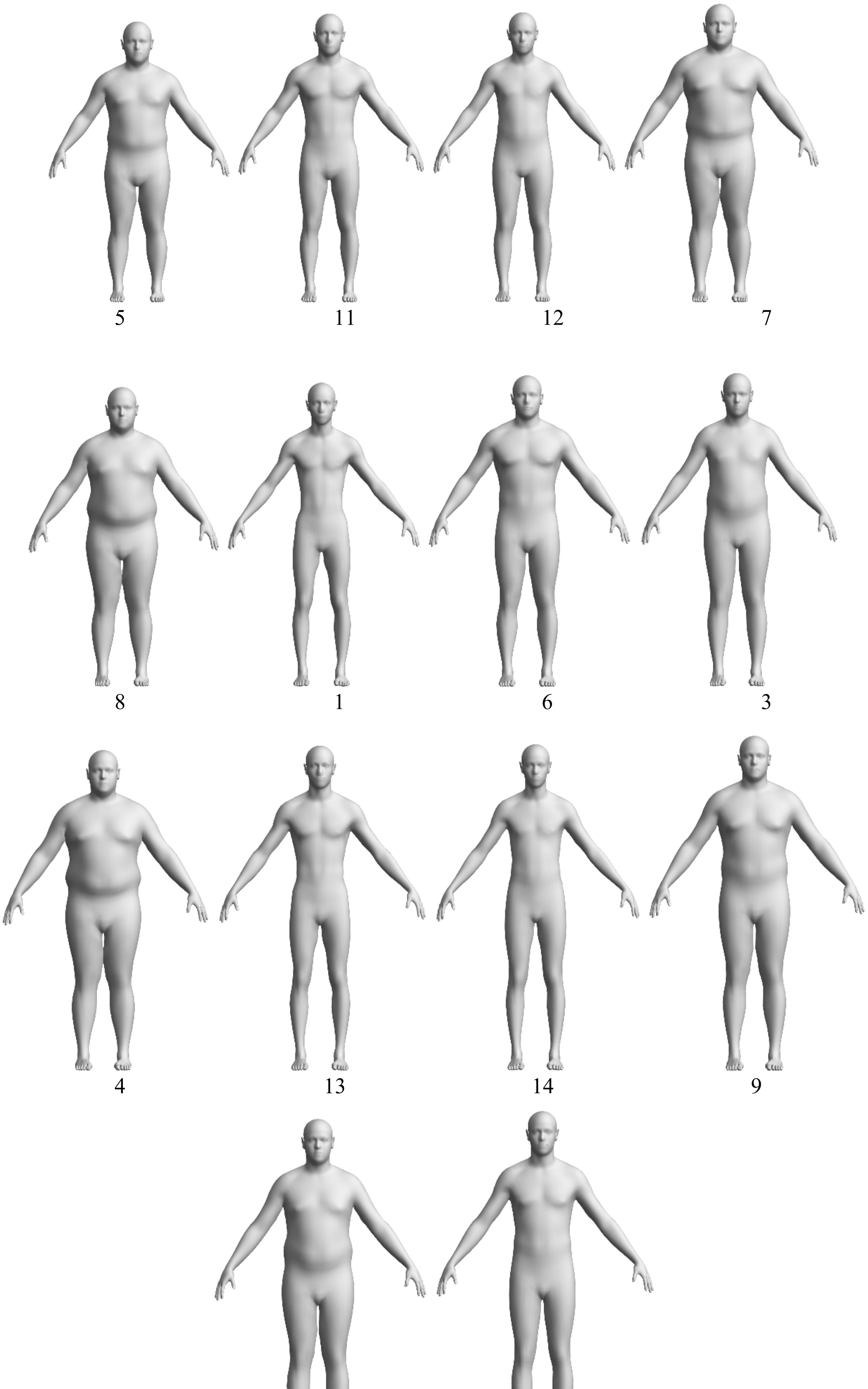

Figure 2. Boundary manikins generated from standard anthropometry. Numbers refer to Table A1.

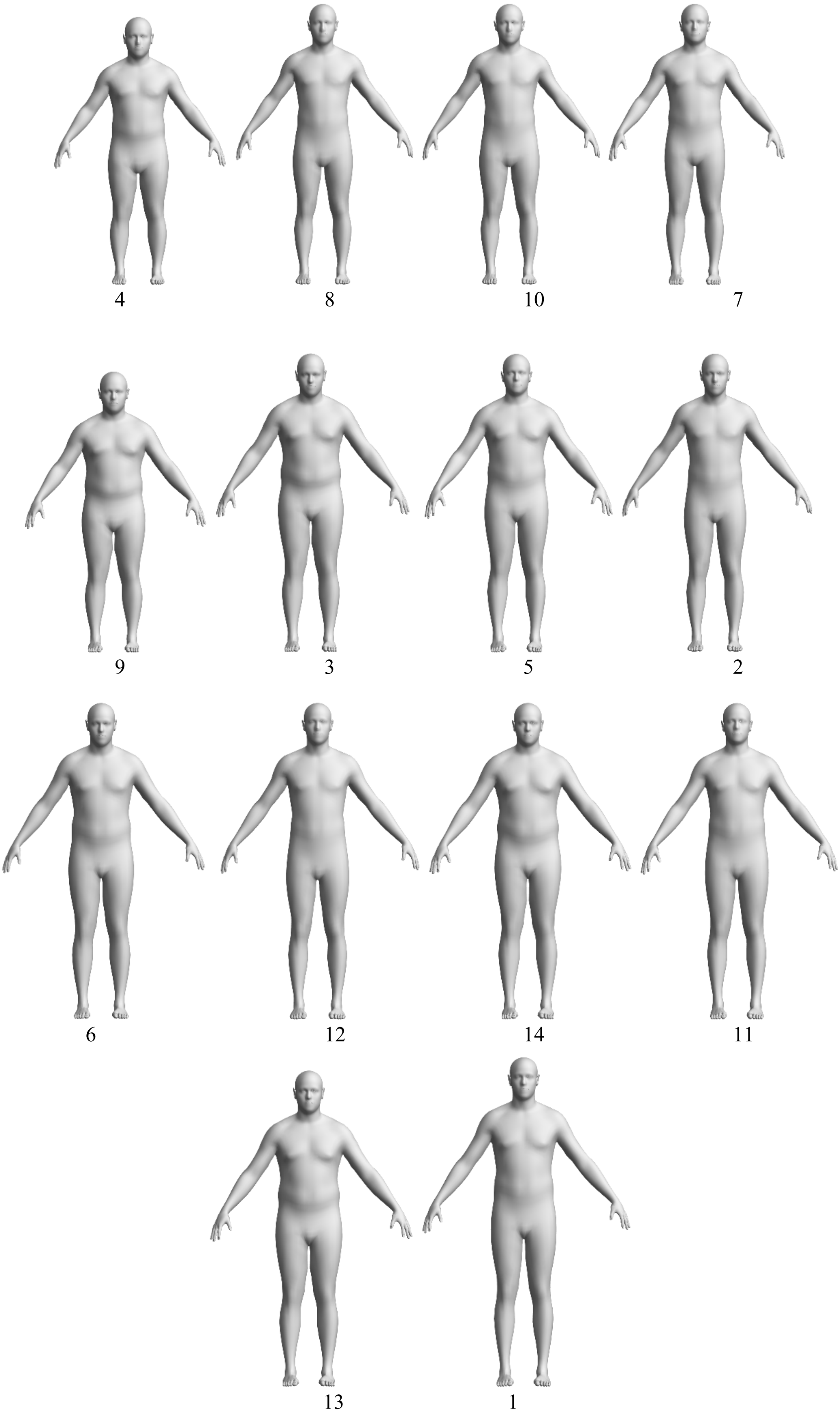

Figure 3. Boundary manikins generated from 3D body shape data. Numbers refer to Table A2.

References

Allen, B., Curless, B., & Popovic, Z. (2004). Exploring the space of human body shapes: Data-driven synthesis under anthropometric control. In Proceedings of Conference on Digital Human Modeling for Design and Engineering. SAE International.

Guan, J., Hsiao, H., Bradtmiller, B., Kau, T., Reed, M. P., Jahns, S. K., Loczi, J., Hardee, H. L., and Piamonte, D. P. T. (2012). U. S. truck driver anthropometric study and multivariate anthropometric models for cab designs. *Human Factors*, 54 (5), pp. 849-871.

Reed, M.P., Park, B-K., Kim, K.H., and Raschke, U. (2014). Creating custom avatars for ergonomic analysis using depth cameras. *Proceedings of the 2014 Human Factors and Ergonomics Society Annual Meeting*. HFES, Santa Monica, CA

Park, B-K and Reed, M.P. (2015). Parametric body shape model of standing children ages 3 to 11 years. *Ergonomics*, 58(10):1714-1725. 10.1080/00140139.2015.1033480

Reed, M.P. and Parkinson, M.B. (2008). Modeling variability in torso shape for chair and seat design. DETC2008-49483. *Proceedings of the ASME Design Engineering Technical Conferences.* ASME, New York

Reed, M.P., and Ebert, S.M (2013). The Seated Soldier Study: Posture and Body Shape in Vehicle Seats. Technical Report UMTRI-2013-13. University of Michigan Transportation Research Institute, Ann Arbor, MI.

APPENDIX

Table A1
Anthropometry PCA Boundary Manikins

Manikin	Stature	BMI	SH/S	Biacromial Breadth	Knee Height, Sitting	Head Circ	Chest Circ	Waist Circ	Hip Circ
1	1701	16.8	0.524	388	529	559	811	619	841
2	1932	24.0	0.505	425	626	585	1028	881	1048
3	1757	26.1	0.521	394	558	566	963	960	1067
4	1806	37.0	0.523	426	582	584	1272	1206	1249
5	1576	29.9	0.541	389	485	557	1054	945	1042
6	1751	27.7	0.525	420	553	576	1119	866	1024
7	1679	34.9	0.535	415	529	573	1227	1074	1148
8	1683	34.0	0.532	400	531	568	1137	1128	1173
9	1885	31.5	0.514	436	610	589	1212	1037	1152
10	1889	30.6	0.511	420	613	584	1122	1091	1177
11	1619	23.3	0.535	393	498	559	961	735	913
12	1622	22.3	0.533	378	501	553	871	789	938
13	1825	19.9	0.514	414	580	575	946	698	917
14	1828	18.9	0.512	399	582	569	856	752	942
Min	1576	16.8	0.505	378	485	553	811	619	841
Max	1932	37.0	0.541	436	626	589	1272	1206	1249
Min%*	0.0%	0.0%	11.4%	5.5%	0.0%	9.3%	0.0%	0.0%	0.0%
Max%	98.7%	98.3%	89.8%	94.5%	97.9%	90.3%	98.3%	98.3%	98.7%

* Percentile relative to original dataset of 236 men.

Table A2
Body Shape PCA Boundary Manikins

Manikin	Stature	BMI	SH/S	Biacromial Breadth	Knee Height, Sitting	Head Circ	Chest Circ	Waist Circ	Hip Circ
1	1938	26.5	0.506	427	629	586	1085	960	1097
2	1755	28.2	0.519	409	562	573	1076	942	1068
3	1751	24.0	0.524	401	552	569	990	839	979
4	1570	27.4	0.541	387	482	556	998	866	993
5	1752	25.7	0.527	405	549	569	1007	883	1022
6	1757	29.8	0.522	412	559	574	1093	987	1111
7	1648	28.1	0.535	397	511	563	1026	911	1040
8	1645	24.8	0.536	391	508	560	966	826	964
9	1650	29.6	0.531	400	519	565	1066	946	1066
10	1647	26.3	0.532	393	515	562	1006	860	990
11	1861	27.6	0.514	420	596	580	1076	966	1100
12	1857	24.3	0.516	414	592	577	1016	880	1024
13	1862	29.1	0.510	423	603	582	1116	1000	1126
14	1859	25.7	0.511	417	600	580	1057	914	1050
Min	1570	24.0	0.506	387	482	556	966	826	964
Max	1938	29.8	0.541	427	629	586	1116	1000	1126
Min%*	0.0%	25.4%	11.9%	11.4%	0.0%	14.4%	17.8%	23.3%	12.7%
Max%	98.7%	78.8%	89.8%	86.4%	98.3%	84.7%	81.8%	80.5%	86.9%

* Percentile relative to original dataset of 236 men.