A basic step towards increased accommodation level accuracy when using DHM tools

D. HÖGBERG*† E. BERTILSSON†‡ and L. HANSON‡

† *Virtual Systems Research Centre, University of Skövde, Skövde, Sweden*

‡ *Department of Product and Production Development, Chalmers University of Technology, Gothenburg, Sweden*

Abstract

The paper addresses the need to consider anthropometric diversity in design and suggests a basic approach for the simultaneous consideration of variance in two key dimensions. This as a basic step from the common, but in many cases poor, approach to use univariate percentile data in design. The bivariate method described can be applied when utilising DHM tools for design in that key dimension values for extreme but likely anthropometric measurement combinations are calculated and entered as input data when representative manikins are defined. The mathematical procedure is described and the outcome of the method is compared to a typical percentile based approach, indicating more accurate accommodation levels being reached by the proposed method. The method is to be seen as a simple method to be used for basic design problems where variance in few anthropometric dimensions are to be considered simultaneously, and not as an alternative for more advanced multivariate methods. The paper takes a pragmatic standpoint, directing its message towards practitioners using DHM tools for design purposes.

Keywords: Anthropometry, Diversity, Accommodation, Manikins, Design.

1. Introduction

There exist many advanced methods for the consideration of anthropometric diversity in design. One example is the development of A-CADRE (Bittner 2000), a collection of 17 manikins that all have different bodily measurements, established with the objective of representing the boundary of the prevalent bodily variety of workstation users. Other advanced methods have been developed for the consideration of posture variation among users, e.g. for vehicle interior design purposes, where both anthropometric and behavioural variation are factors in the model (Garneau and Parkinson 2009). Using such methods in design is likely to gain the ergonomic qualities of the object being designed, be it products, vehicles or workstations. Still, a study in Swedish vehicle manufacturing companies gave that it was common to use only a few human models as virtual test persons when designing workstations or evaluating manual work (Bertilsson et al. 2010). Typically a small female and a large male, according to stature, were considered as sufficient when performing ergonomics evaluations using DHM tools. This approach means that one key measurement is used (stature) and that two boundary manikins are used (one small female and one large male). The study gave that a common argument for this rough approach was the time needed for each extra virtual test person to be included in the simulation, and that this extra time was not considered worth the possible increase in accuracy in assessing and meeting set accommodation levels. Also, the study gave that the comprehension of the complexity of anthropometric diversity in design, and ways to deal with it, was rather scarce, which may also be a reason for the rough approach utilized in the industries studied. This is no ground breaking news though, and similar concerns have been dealt with for many years (Daniels 1952; Roebuck et al 1975) and more recently (Ziolek and Wawrow 2004; Robinette and Hudson 2006).

There may be many reasons for this gap in best practice, reported in literature by the research society, and observed industry practice, but traditions of how to perform DHM based simulations, and lack of DHM tool usability, are believed to be two important ones. So, the question rises of how to improve industry practice when using DHM tools (in cases when needed that is). One way would be “to make it easier to do it right”. Indeed, DHM tools’ ability to, in theory at least, model any existing anthropometric configuration ought to be utilized when performing simulations of

*Corresponding author. Email: dan.hogberg@his.se

human-product interactions. One step in the direction to aid designers to consider anthropometric diversity is the approach taken when developing the IMMA manikin software (Hanson et al. 2010), where the standard way to perform a simulation include an almost automatic definition of several anthropometrically representative virtual test persons (a manikin family that represents variance of a number of key measurements) followed by an automatic batch simulation using all these manikins.
Still, as this paper will show, one can consider two dimensions simultaneously by doing some basic mathematical treatments of the anthropometric data of the targeted user group. This approach is assumed to be applicable for any DHM tool being used, in the way that the method calculates extreme, but realistic, dimensions of two key measurements, acting as input data for regression equations in the DHM tool, used to define the manikin's other measurements. This as a small but important step from using the univariate (one-dimensional) approach, which in most design purposes is poor in representing anthropometric diversity. Using the bivariate (two-dimensional) approach one can define a number of boundary manikins that concurrently represent variance in, for example, *stature & weight*, or *stature & sitting height* etc. As noted, the approach defines boundary cases, and for some design purposes it might be relevant to define distributed cases instead, or as well. These categories of *cases* are further described in (HFES 300 Committee 2004). However, as much as that book is instructive, it does not contain details of how to calculate boundary cases for bivariate distributions. This paper aims to accompany in that respect, and the paper takes a pragmatic standpoint, directing its message towards practitioners and students using DHM tools for design purposes, possibly being non-specialists in ergonomics or anthropometry.

2. Materials and Methods

The confidence ellipse method is used for defining appropriate boundary manikins according to two selected key dimensions and a desired accommodation level, here represented by the confidence region. Assuming that both dimensions are normal distributed, which is appropriate in most cases (Pheasant and Haslegrave 2006), general statistical methods are applied to analyse the data (e.g. Sokal and Rohlf 1995; Brandt 1999).
The ANSUR anthropometric data is used in the examples (Gordon et al. 1989). This data is somewhat dated and limited in terms of representing "average people" (in that it is based on army personnel measurements), but considered relevant here in that it covers data of a large set of measurements and individuals. The method presented is applicable using any well founded anthropometric data though. Figure 1 shows a scatter matrix of the ANSUR data for stature and weight for male population.

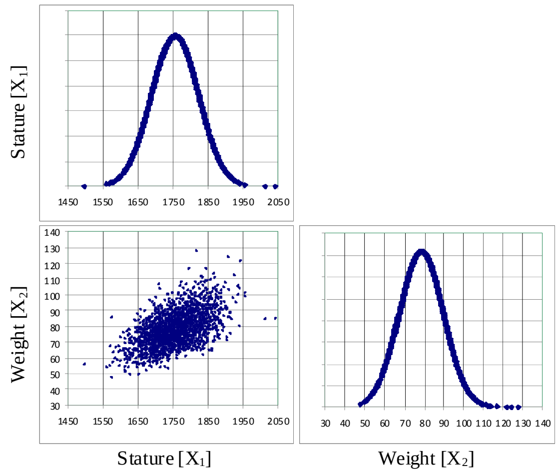

Figure 1: Scatter plot matrix of stature (mm) and weight (kg) for ANSUR data for male population.

2.1. Mathematical procedure

The bivariate normal distribution can be denoted (**X**)~N(**μ**,**Σ**) where:

X is the random vector $\begin{bmatrix} X_1 \\ X_2 \end{bmatrix}$

μ is the mean vector $\begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}$

Σ is covariance matrix $\begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$

where:
σ_{11} is the variance = σ_1^2
σ_{22} is the variance = σ_2^2
$\sigma_{21} = \sigma_{12}$ is the covariance = $\rho\sigma_1\sigma_2$
(μ_1 and μ_2 are the mean values, σ_1 and σ_2 are the standard deviations and ρ the correlation coefficient)

The eigenvalues λ of covariance matrix **Σ** are calculated to define the size of the confidence ellipse. The eigenvalues are given by studying the determinant and solving the following equation:

$$\det(\mathbf{\Sigma}-\lambda\mathbf{I})=0 \tag{1}$$

where:

I is the identity matrix = $\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

Equation (1) has the solutions:

$$\lambda_{1,2}=\frac{\sigma_{11}+\sigma_{22}}{2}\pm\sqrt{\frac{(\sigma_{11}-\sigma_{22})^2}{4}+\sigma_{12}{}^2} \quad (2)$$

The length of the semi-major axis of the ellipse is $\sqrt{\lambda_1}$ and the length of the semi-minor axis of the ellipse is $\sqrt{\lambda_2}$, where $\sqrt{\lambda_1} > \sqrt{\lambda_2}$.

The eigenvector **x** is calculated in order to find the direction of the semi-major and semi-minor axis of the confidence ellipse. The eigenvector is determined by solving the following equation:

$$\mathbf{\Sigma x}=\lambda \mathbf{x} \quad (3)$$

where:

x is the eigenvector = $\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

Following equation can be drawn from (3):

$$x_2=\frac{x_1(\lambda_1-\sigma_{11})}{\sigma_{12}} \quad (4)$$

Value for x_2 can be calculated by setting x_1=1 in (4).

The angle θ of the semi-major axis (in relation to the x axis) and the semi-minor axis (in relation to the y axis) of the ellipse can be calculated by:

$$\tan\theta=\frac{x_2}{x_1} \quad (5)$$

The ellipse defined by the axes $\sqrt{\lambda_1}$, $\sqrt{\lambda_2}$ and the eigenvector **x** represents a confidence region of approximately 39.4%. To obtain the expected confidence level the axes are scaled up by letting:

$a = k\sqrt{\lambda_1}$

$b = k\sqrt{\lambda_2}$

where k is calculated from the chi-squared (χ^2) distribution:

$$k=\sqrt{\chi_p{}^2(1-P)} \quad (6)$$

meaning that a is the length of the semi-major axis and b the length of the semi-minor axis of an ellipse that provides the desired confidence level. P represents the probability level (e.g. P=0.9 for a 90% confidence region), and *p* represents degrees of freedom, i.e. two in this case. Table 1 gives k values for common probability levels for *p*=2.

Table 1: Scale factor k for common probability levels for two degrees of freedom.

Probability, P	0.90	0.95	0.99
Scale factor k	2.146	2.447	3.035

The ellipse defined by using raw data can be used to define theoretically plausible boundary cases. However, it is recommended to standardise the raw data into dimensionless z-scores (standard scores) before building the ellipse and defining cases. This is done by letting:

$$z=\frac{X-\mu}{\sigma} \quad (7)$$

This standardisation procedure render standard normal distributions, meaning that mean values are 0 and variances and standard deviations are 1. This procedure is appropriate when comparing different normal distributions (Glenberg and Andrzejewski 2007) and gives each distribution the same significance in the calculations. Both procedures give the same confidence ellipses (when represented in each particular two-dimensional "space"), but when defining cases at axis end points the two procedures does not give the same cases. Hence, standardisation is recommended.

3. Results

3.1. Example 1

Figure 2 shows the confidence ellipse obtained when entering raw data (i.e. non-standardised data) from the ANSUR database for stature (x axis) and weight (y axis) for male population and a confidence region of 90%. Stature and weight were selected as variables in this example since most people are familiar with their own stature and weight data, making interpretation of Figure 2 easier.

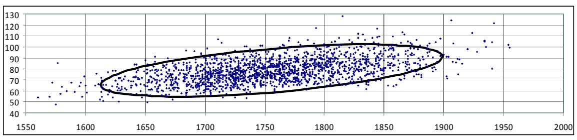

Figure 2: Confidence ellipse plotted in real space for stature and weight for ANSUR data male population with P=0.9 (scales in mm and kg).

Figure 3 shows the corresponding ellipse based on standardised data. This ellipse can for example be used to define theoretically plausible boundary cases at the axis end points, as shown by case 2,3,4,5 in Figure 3 (more cases can of course be defined). Measurement values (i.e. values transformed from z-scores), z-scores and percentile values for the four boundary cases, as well as one mean case (case 1) defined at the ellipse centre, are given in Table 2.

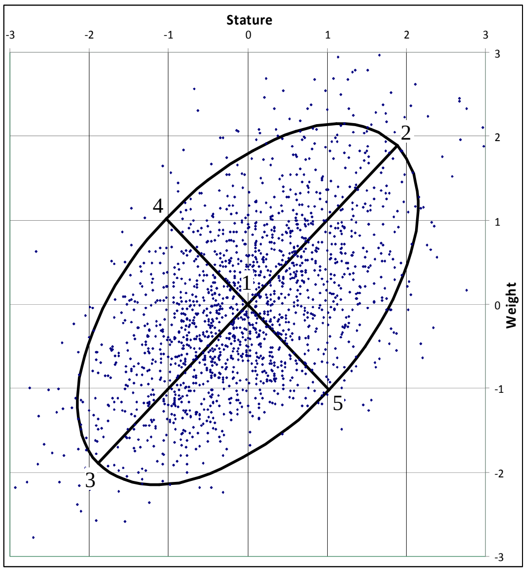

Figure 3: Four boundary cases defined at axis end points and one mean case (scales in standard scores).

Table 2: Data for the five cases.

Case	Measurement	Value (mm/kg)	z-score	%-ile
1	Stature	1756	0	50
	Weight	78.5	0	50
2	Stature	1882	1.89	97.0
	Weight	99.4	1.89	97.0
3	Stature	1630	-1.89	3.0
	Weight	57.5	-1.89	3.0
4	Stature	1688	-1.02	15.3
	Weight	89.8	1.02	84.7
5	Stature	1824	1.02	84.7
	Weight	67.1	-1.02	15.3

To illustrate, entering the values of stature and weight (Table 2) in the DHM tool Jack gives manikins as shown in Figure 4. All other manikin measurements are regressed from entered stature and weight values. In this case these manikins represent the suggested virtual test group to use for design purposes in ergonomics simulations.

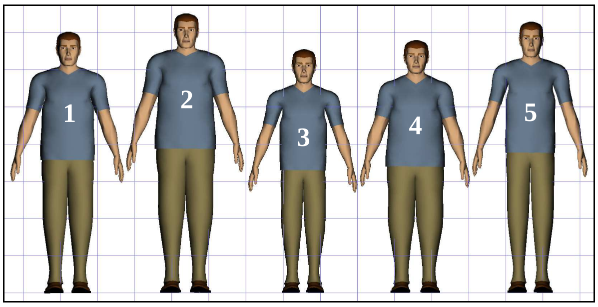

Figure 4: The five cases modelled in Jack.

3.2. Example 2

In this example the confidence ellipse approach is compared with the approach (here named *percentile approach*) where both key dimensions are set to a specific percentile value (e.g. 5%-ile and 95%-ile, hereby mistakenly assuming 90% accommodation coverage). The method of comparison is by using the manikins defined by each approach in a design task in the DHM tool Jack. In this case the key measurements are chosen as stature and sitting height (i.e. these two dimensions are considered to be two dimensions strongly affecting the design task). Figure 5 shows the confidence ellipse for stature (x axis) and sitting height (y axis) based on the ANSUR database, for females and P=0.9. Figure 5 also shows an imaginary square accommodation region formed by the 90% confidence intervals for each dimension separately. In reality one typically only uses the lower left case B (5%-ile in both dimensions) and the upper right case A (95%-ile in both dimensions) in simulations since the other two cases, C and D, are unlikely measurement combinations to exist in reality (as the scatter plot in Figure 5 suggests). Worth noting is that the ellipse theoretically encloses 90% of the individuals, whereas the square area encloses approximately 85% of the individuals in this case. Additionally, the area of the ellipse is approximately 12% less than the area of the rectangle in this case.

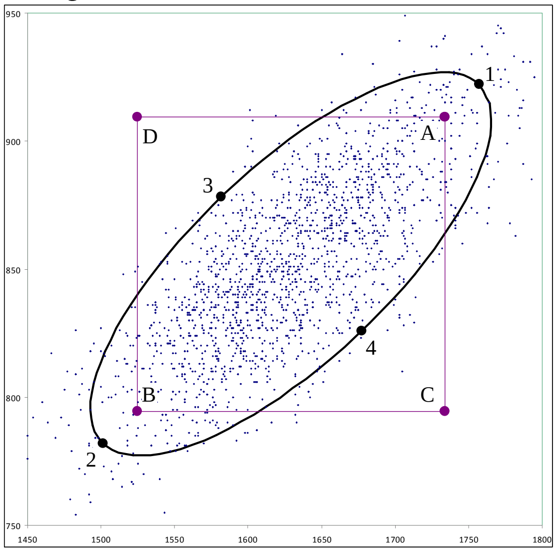

Figure 5: The bivariate confidence ellipse as well as the square region shaped by the two univariate confidence intervals (scales in mm).

Values for stature and sitting height for cases 1,2,3,4 and A,B in Figure 5 are given in Table 3.

Table 3: Values for cases 1,2,3,4 and A,B.

Case	Measurement	Value (mm)	z-score	%-ile
1	Stature	1757	2.01	97.8
	Sitting height	922	2.01	97.8
2	Stature	1502	-2.01	2.2
	Sitting height	782	-2.01	2.2
3	Stature	1582	-0.75	22.6
	Sitting height	878	0.75	77.4
4	Stature	1677	0.75	77.4
	Sitting height	826	-0.75	22.6
A	Stature	1734	1.64	95
	Sitting height	909	1.64	95
B	Stature	1525	-1.64	5
	Sitting height	795	-1.64	5

Figure 6 shows these six manikins modelled in Jack adopting the predetermined “seated typing” posture, all experiencing the same level of comfort.

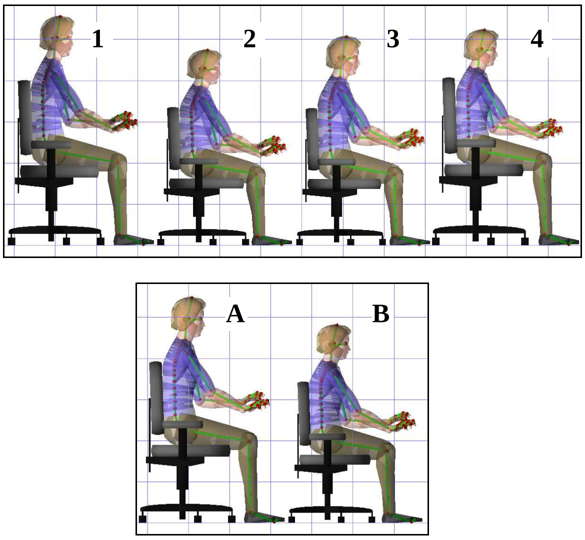

Figure 6: Manikins 1-4 and A-B in seated posture.

Table 4 shows the approximate adjustment ranges required to accommodate manikin 1,2,3,4 and A,B, exemplifying an office workplace design task, considering seat height, table top height and eye height (the latter e.g. for defining height adjustment of a computer screen, assuming fixed line of sight angle).

Table 4: Approximate adjustments ranges drawn from manikins 1,2,3,4 and A,B respectively.

	Seat height (cm)	Table height (cm)	Eye height (cm)
Manikins 1,2,3,4	9	15	18
Manikins A,B	6	12	15

4. Discussion

Table 4 shows larger adjustment ranges required to accommodate the targeted population for the confidence ellipse method compared to the percentile approach. This is not surprising since the confidence ellipse method renders more extreme cases than the percentile approach (Figure 5 and Table 3). However, it is argued that the confidence ellipse method more accurately creates cases that represent the intended accommodation level. Hence, the upper adjustments ranges in Table 4 would be more appropriate to use as design data rather than the lower ones, since using the lower ones do not provide the expected level of accommodation (approximately 85% rather than the desired 90%).

Of course, people vary in more dimensions than two, and design tasks may require the consideration of anthropometric diversity in more than two dimensions. Indeed, Equations (1), (3) and (6) are also applicable for multidimensional approaches. Still, this paper encourages at least taking the initial step from univariate to bivariate anthropometric consideration in design.

One obvious advantage with the bivariate approach compared to multivariate approaches is the simplicity in the mathematical calculations required, e.g. easily computed in a regular spreadsheet software. Another advantage is the ease to interpret the results obtained, especially if an ellipse is plotted along with a scatter plot (as in Figure 2, 3 and 5), where one visually can decode the calculation results, including the case definitions, in their seemed correctness and meaning. This is not as easy for, say, a four-dimensional ellipsoids or PCA based approaches. However, the application of multivariate analysis methods, dimensionality reduction methods (such as Principal Components Analysis) and other sophisticated methods are at times advantageous in design for the consideration of anthropometric variation among targeted users, e.g. as reported in (Meindl et al. 1993, Bittner 2000; Garneau and Parkinson 2009).

5. Conclusion

The paper argues that the proposed bivariate method is advantageous compared to approaches based on the use of univariate percentile data in design, where the proposed method is recommended as a basic step towards enhanced accuracy in meeting desired levels of accommodation, e.g. when using DHM tools for the design of products and workplaces.

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