EFFECTS OF A DATA REDUCTION TECHNIQUE ON ANTHROPOMETRIC ACCOMMODATION

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Multivariate data reduction techniques such as principal components analysis (PCA), offer the potential of simplifying the task of designing and evaluating workspaces for anthropometric accommodation of the user population. Simplification occurs by reducing the number of variables that one has to consider while retaining most, e.g. 89%, of the original dataset's variability. The error introduced by choosing to ignore some (11%) of the variability is examined in this paper. A set of eight design mannequins was generated using a data reduction method developed for MIL-STD-1776A. These mannequins, which were located on the periphery of a circle encompassing 90%, 95% and 99% of the population on two principal components, were compared with the true multivariate 90%, 95% and 99% of the population. The PCA mannequins were found to include less of the population than originally intended. The degree to which the mannequins included the true percentage of the population was found to depend mainly on the size of the initial envelope (larger envelopes were closer to the true accommodation limits). The paper also discusses some of the limitations of using limited numbers of test cases to predict population accommodation.

INTRODUCTION

The inadequacy of applying univariate hropometric data to multivariate problems has en shown in several ways (Moroney & Smith, 72; Bartholomew, 1980; NASA, 1978). The basic oblem is that correlations are relatively low tween anthropometric dimensions, and univariate thods do not take this fact into account. As a ult, designers unwittingly exclude larger rcentages of the population than originally ended. For instance, Moroney showed that 53%, her than 10%, of a sample were excluded when and 95th percentile limits were applied to 13 thropometric dimensions. In light of this, one can why it is essential to include correlations enever two or more anthropometric dimensions considered simultaneously, and this is reflected current military standards.

The problem, when dealing multivariate nstructs, is that as the number of anthropometric mensions increases, so does the complexity of the alysis and of the interpretation of the results. Fortunately, data reduction techniques, such as factor analysis, exist that can greatly simplify the problem while keeping correlations into account. Factor analysis can reduce the original set of variables to a smaller more manageable set, while accounting for most of the variability. This distillation of data can be a tremendous advantage in the design and/or evaluation of workspaces or clothing, but there is a price to pay for simplification. Users should understand the underlying assumptions and limitations before reaching conclusions on the basis of a reduced dataset.

The purpose of this paper is to explore some of the limitations of factor analysis, more particularly with respect to its ability or inability to guarantee a degree/percentage of population accommodation.

BACKGROUND

Depending on the degree of correlation between variables and the choice of factors, factor analysis may be used to reduce the original set of variables while explaining 80% or more of its variability. This reduction simplifies the problem considerably and allows designers to focus on the most important elements. Bittner proposed a combination of factor analysis and conventional percentile "template-mannequin" approach (Bittner, 1976) in which a mid-point (50th percentile) and two extremes (e.g. 5th and 95th percentiles) were used as test cases. The philosophy of the univariate percentiles, i.e. if an items fits the extremes it should fit those in-between, was extended to multiple variables. Bittner's technique consisted of reducing the dimensionality of the space through factor analysis and selecting a centroid mannequin (equivalent to 50th percentile) and uniformly spaced extremes located on the surface of an equiprobability ellipsoid containing, say, 90% of the population. This concept has gained momentum in recent years, with refinements and applications in workspace design (Kennedy & Zehner, 1995; Meindl, Hudson, & Zehner, 1993), clothing/equipment design (Gordon, Corner, & Brantley, 1997) and military specifications (MIL-STD-1776A, 1994).

At least two validation studies were performed on Bittner's methodology using 2D modeling. In both cases, an aircraft cockpit was designed in such a way as to accommodate Bittner's *cadre* of 17 mannequins. The cockpits were subsequently tested using either raw data (Bittner, Wherry, Glenn, & Harris, 1986) or artificially (Monte Carlo) generated mannequins (Hendy, 1990). Although the process was similar, the outcomes were substantially different. In one case the simulated accommodation levels exceeded 98%, while in the other they were much less than 90% once all interferences were accounted for. One of the reasons for this discrepancy is the fact that accommodation implies many types of interaction between individuals and their workspace. Therefore, differences in workspace constraints (e.g. seat adjustment type or downward vision angle requirements) are likely to cause differences in accommodation levels, even when the same *cadre* of mannequin is used in the design stages.

To avoid confounding the effect of workspace design, the approach used in this paper focuses more on the theoretical aspects of this technique rather than the practical application.

METHOD

The six anthropometric dimensions used in this study were those specified in MIL-STD-1776A and used in the JPATS (Joint Primary Training Aircraft), namely: sitting height, acromial height sitting, eye height sitting, buttock-knee length, knee height sitting and functional reach. The 1985 survey of Canadian aircrew (Stewart, 1985) was used as the source of raw data, and Statistica™ (Statsoft, 1997) was used to perform the principal components analysis with the correlation matrix as input. Two principal components were retained, explaining 89% of the variability of the six anthropometric variables. A normalized varimax rotation of the two component axes was performed. Interpretation of the principal components after rotation showed the first component to be consistent with trunk-related variables, and the second with limbs (Table 1).

Table 1 Factor loadings (Varimax rotation)

Variable	Factor 1	Factor 2
Sitting height	0.93	0.29
Eye height sitting	0.94	0.23
Acromial height sitting	0.88	0.30
Buttock-knee length	0.24	0.90
Knee height sitting	0.34	0.88
Functional reach	0.28	0.85

Following the methodology outlined by Meindl *et al* (1993), eight mannequins were selected (every 45 degrees) around circles encompassing 90, 95 and 99 percent of the aircrew population. The size of the circle was determined empirically from the factor scores of the raw data. In parallel to this, the 1985 aircrew population was "filtered" multinormally (on all six variables) so that subsets representing the true 90, 95 and 99 percent of the population could be used for comparison with the PCA mannequins.

The three sets of eight mannequins were converted back to anthropometric measurements from their factor scores. The anthropometric data were plotted in 2D with variables highly loaded with the first principal component on the *x*-axis and those highly loaded with the second on the *y*-axis. An ellipse was fitted through the eight mannequin points to help visualize the implied theoretical inclusion/exclusion limits of the PCA. The graphs consist of mannequin points and their associated ellipse plotted over the true multivariate percentage of aircrew.

RESULTS

Figures 1, 2 and 3 show the location of the mannequins generated through principal components analysis for nominal accommodation values of 90%, 95% and 99%, in relation to the equivalent true multivariate percentage of the 1985 aircrew survey population. These figures compare, in a bivariate way, two anthropometric variables: buttock-knee length, with a 0.93 loading on factor 1, and sitting height, with a 0.90 loading on factor 2.

The theoretical accommodation of the PCA mannequins was calculated using the multivariate normal probability density function. The mannequins were found to lie on a hyper-ellipse encapsulating the percentage of the population shown in Table 2.

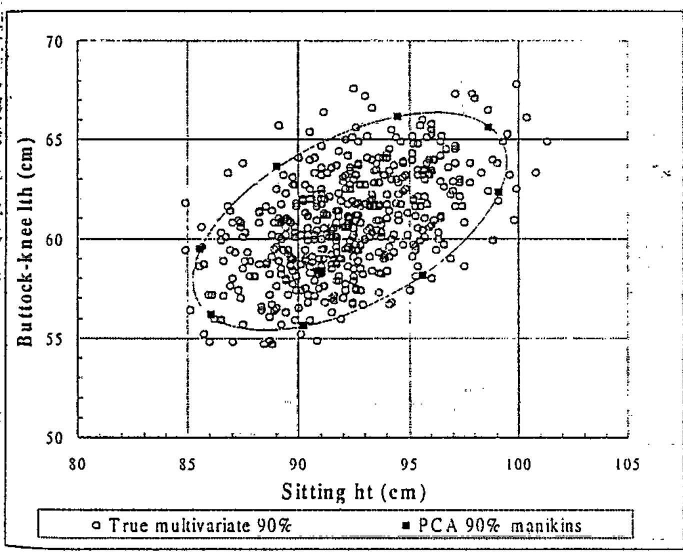

Figure 1 Comparison of 90% PCA mannequins ellipse with the true 90% of the same population.

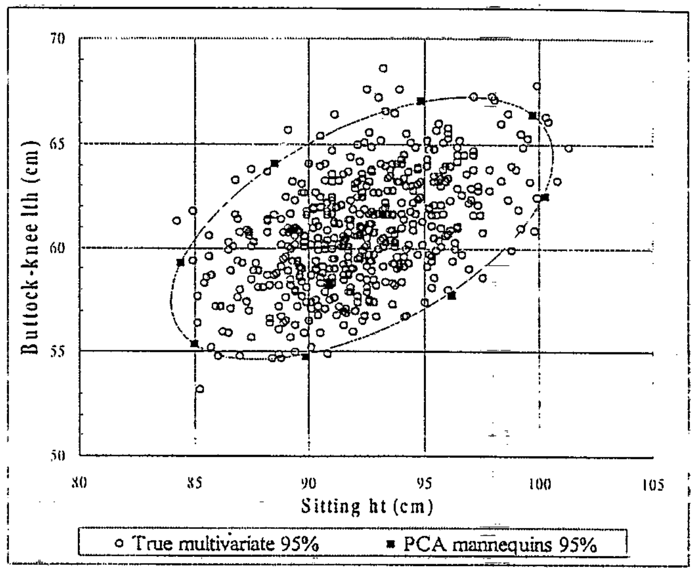

Figure 2 Comparison of 95% PCA mannequins ellipse with the true 95% of the same population.

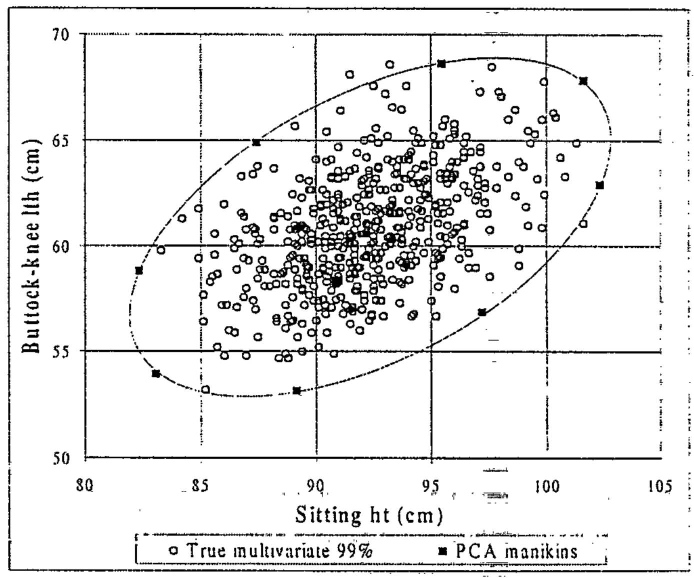

Figure 3 Comparison of 99% PCA mannequins ellipse with the true 99% of the same population.

Table 2 Theoretical multivariate accommodation levels.

Theoretical accommodation level		
Multinormal	**PCA**	**Difference**
90%	39%	51%
95%	59%	36%
99%	86%	13%

DISCUSSION

While principal components analysis and the methodology used to derive boundary mannequins may provide an efficient way of characterizing the population, the price to pay for the simplification is the loss of some of the variability. This loss becomes apparent when mannequins are converted from the principal components analysis (PCA) back to anthropometric variables. Figures 1, 2, and 3 show that fairly substantial portion of the population to be accommodated is outside the limits defined by the PCA mannequins. The results presented in Table 2, and supported in Figures 1, 2, and 3, show that the relative exclusion percentage decreases significantly with increases of the target accommodation percentage.

The mannequin selection mode used in the method, i.e. selection of points around an equiprobability circle, seems to imply that satisfying those points would be a necessary and sufficient condition to guarantee accommodation of that percentage of the population. This, as shown in Hendy (1990), is not necessarily the case. Exclusion zones can be one-tailed univariate or complex multivariate in nature. Figure 4 shows three hypothetical exclusion zones. Zone 1 is a complex exclusion zone that would likely go undetected by confining the fit testing to only eight mannequins. Zone 2 represents a complex exclusion zone that one of the mannequins may attract attention to. Zone 3 is a simple univariate exclusion zone affecting two mannequins. In the first case, the technique failed to detect a potential problem. In the second and third cases the technique identified a problem but is unable to determine its impact on population accommodation.

Critical variables are a function of the interaction between the individual, and what (s)he has to do, and the specific workspace. The *a priori* selection of critical variables, i.e. those variables for which less than 100% of the population is accommodated, presupposes intimate knowledge of the workspace. This selection is an important consideration. The PCA method is a data reduction method that does not take into account the criticality of the anthropometric variables relative to the workspace, but their correlation and variability. Therefore depending on whether the six variables selected *a priori* are truly critical in a particular workspace design, the actual accommodation percentage could be higher (if no other variable was critical) or lower (if an unsuspected variable turned out to be critical) than the targeted accommodation levels. The exclusion zones shown in Figure 4 could, in fact, be the result of critical variables other than those selected in the analysis.

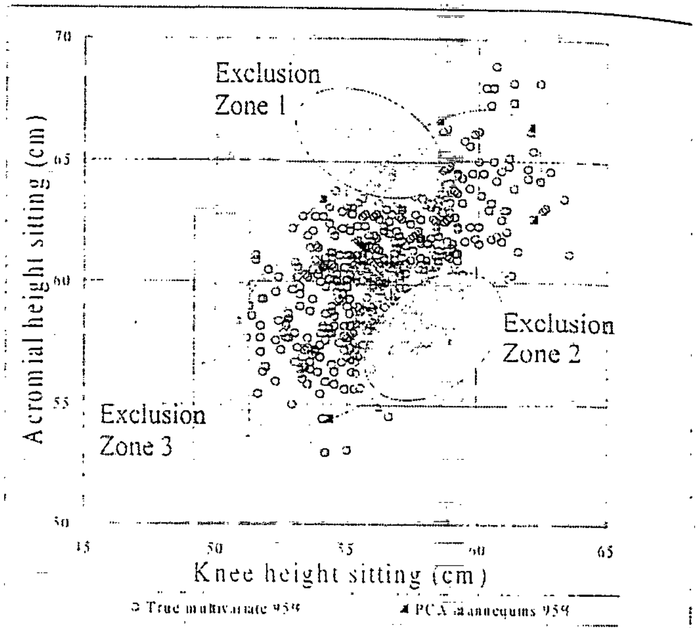

Figure 4 Hypothetical workspace exclusion zones relative to PCA mannequins.

CONCLUSIONS AND RECOMMENDATIONS

The ultimate value of a method is measured by its ability to predict accommodation with accuracy and diagnose potential problems. As in any problem dealing with probabilities, there is always uncertainty associated with predictions. The PCA method is a practical tool that can be used to reduce multivariate data to its simplest expression, but it requires knowledge of the underlying assumptions and their effect on the outcome. The following potential sources of error associated with the PCA method were identified:

1. Number of mannequins. In the example used in this paper, the PCA method reduced a six-dimensional population accommodation problem down to a two-dimensional problem with eight points. This is an extraordinarily efficient use of eight points, but it remains an extremely small number of individuals to represent an entire population.

2. Size of the accommodation envelope. The results of this study show the need for selecting a large percentage of the population in the principal components distribution. The traditional 90% accommodation target, coming from the old 5th to 95th criteria, is clearly insufficient as a first step.

3. Choice of variables. The PCA method relies on the *a priori* selection of critical variables. One of the problems is that critical variables cannot always be determined until after the initial workspace evaluation. One should not lose sight of the fact that "surprise" critical variables can invalidate the population accommodation estimates.

4. Detection of exclusion zones. Exclusion zones may or may not be detected by any of the mannequins selected. In the event of the identification of exclusion zones by one or more of the mannequins, a more exhaustive technique is required to determine the extent of the problem.

The PCA method in and of itself does not appear to be sufficient to guarantee a targeted level of population accommodation. A certain amount of risk, large or small depending on the situation, remains after such an analysis. Increasing the size of the initial accommodation envelope, the number of mannequins, and the number variables can help reduce this risk. The ideal scenario would employ PCA in the initial stages of design and evaluation, and would verify the population accommodation through the use of large-scale fitting trials or simulations thereof. Under real world constraints, man-models may be the only feasible means of achieving this.

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