Predicting Seated Body Shape from Standing Body Shape

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Abstract

A large amount of body surface scan data in standing postures is available from population surveys, but relatively little data in supported seated postures has been gathered. This paper presents a method for predicting seated body shape in a posture typical of automobile driving using data from a standing scan. A principal component analysis (PCA) of template-fitted standing data for 120 women was conducted and 60 PCs were retained. Data for the same women in a seated posture were analyzed using the same technique. A regression analysis was conducted predicting seated PC scores from standing PC scores and the method was evaluated by comparing predicted and measured body shapes for 18 women with a wide range of body size measured in a separate study. The method was found to produce accurate predictions of surface shape, with median errors less than 5 mm after accounting for posture differences. The method shows promise for obtaining predictions of alternative postures for populations for which only a few postures have been scanned.

Keywords: body scanning, body shape modeling, standing postures, seated postures

1. Introduction

The most common scanning posture used in three-dimensional (3D) anthropometry studies is a standing pose with the feet about 200 mm apart and the arms abducted from the side of the body. Many studies also include an unsupported seated posture. Methods have been developed for extracting standard anthropometric measures from these and similar postures, and many studies have developed statistical body shape models from scan data gathered in these postures.

However, because most work tasks and product interactions occur in postures that are different from the scanned postures, methods are needed to generalize the 3D data to other postures. One approach is to select standard anthropometric dimensions from the scan data and input those values to human modeling software, such as Jack or RAMSIS. The resulting manikins can then be articulated to a wider range of alternative postures. The resulting body shapes are not necessarily representative outside of the areas quantified by the extracted standard anthropometric dimensions, but this approach leverages the large amount of functionality in these commercial human modeling tools (Reed et al. 2014).

An alternative is the development of statistical body shape models based on the scan data rather than extracted dimensions. Many such models have been reported (e.g., Allen et al. 2004; Reed and Parkinson 2008; Hasler et al. 2009). Recent examples include Loper et al. (2015) and Reed and Park (2015). Reed et al. (2014) developed a statistical body shape model based on the surface mesh of a widely used DHM tool, enabling rapid implementation. However, the statistical model did not include the effects of body shape change with posture change away from the scan posture.

Among the statistical body shape models, only a relatively small number are capable of representing posture change. The most sophisticated of these provide a smooth transformation across a wide range of postures (e.g., Loper et al. 2015). However, these methods have not found widespread use for ergonomics analysis because of the challenges of implementing the models in ergonomics software. In particular, the implementation of the surface blending functions that simulate the effects of posture change are linked to particular kinematic models. When implemented with different kinematic models (for example, different joint angle definitions and different joint locations relative to the surface) the blending functions are no longer accurate.

This paper describes a statistical method of generalizing postures without the requirement for a kinematic linkage and joint blending functions. We

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use a dataset with multiple postures to learn the within-subject relationships in body shape in multiple postures and demonstrate that it is effective in predicting automotive-like seated postures from standing scan data.

2. Materials and Methods

2.1. Data Source

The data for this analysis were drawn from a study of 100 men and 100 women with a wide range of body size and age (Reed and Ebert 2013). Approximately 30% had a body mass index >30 kg/m^2. Unusual for a body scan study, about half of the study population was over age 60 years.

The current analysis is based on data from 73 women who were scanned using a VITUS XXL laser scanner in both a standing posture and a supported seated posture similar to an automobile driving posture. Figure 1 shows the scan postures.

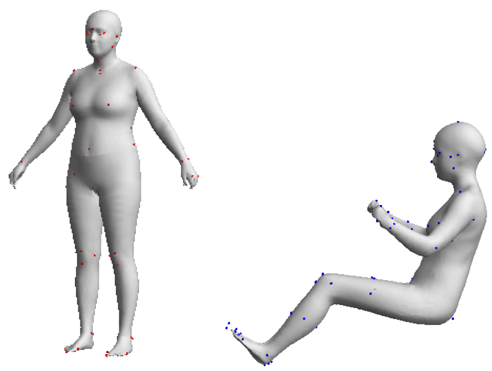

Figure 1. Standing and seated postures used for the current analysis.

The scan data were processed through a pipeline that included hole-filling and decimation to approximately 80k vertices from ~200k vertices in the original scans. Mesh templates were fit to the scans using procedures described in Park and Reed (2015). The templates for the standing and seated scans were different, including different numbers of vertices and polygons, and no homologous mapping was established between the two templates.

2.2 Analysis

Figure 2 shows the overall analysis process. Principal component analyses (PCA) were conducted separately for the standing and seated data, using methods described in Reed and Parkinson (2008). For the current purposes, 60 PCs representing more than 99% of the variance in the vertex coordinates were retained for each model.

In typical applications, body shapes are predicted from overall anthropometric measures such as stature and body weight (Parkinson and Reed 2008; Park and Reed 2015). We construct statistical body shape models by conducting regression analysis to predict principal component (PC) scores and reconstruct a body shape from the PC scores.

For the current work, we used PC scores from the standing posture to predict the scores in the seated posture via linear regression. Note that the standing and seated postures were not combined in the same analysis until this step, so the PC scores are from different bases (indeed, the meshes are different).

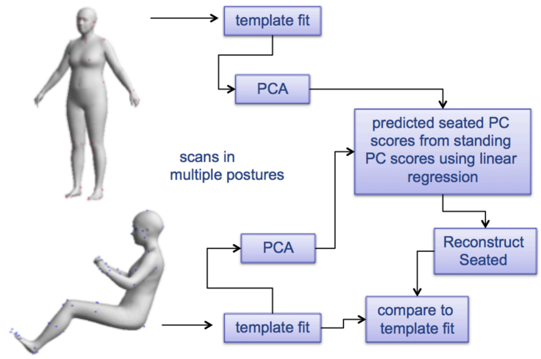

Figure 2. Schematic of analysis method.

3. Results

Figure 3 shows some examples of the results of the seated predictions. Each illustration shows the standing template fit, the seated template fit, and the predicted seated body shape generated from applying the regression model to the PC scores from the standing fit.

In general, the predicted body shapes are very similar to the measured shapes. The significant discrepancies arise from posture differences in the seated scans that are unrelated to body size and shape, and hence not predictable from the standing data. For example, some individuals sat with more cervical or lumbar spine flexion than the mean expected given their standing body shape.

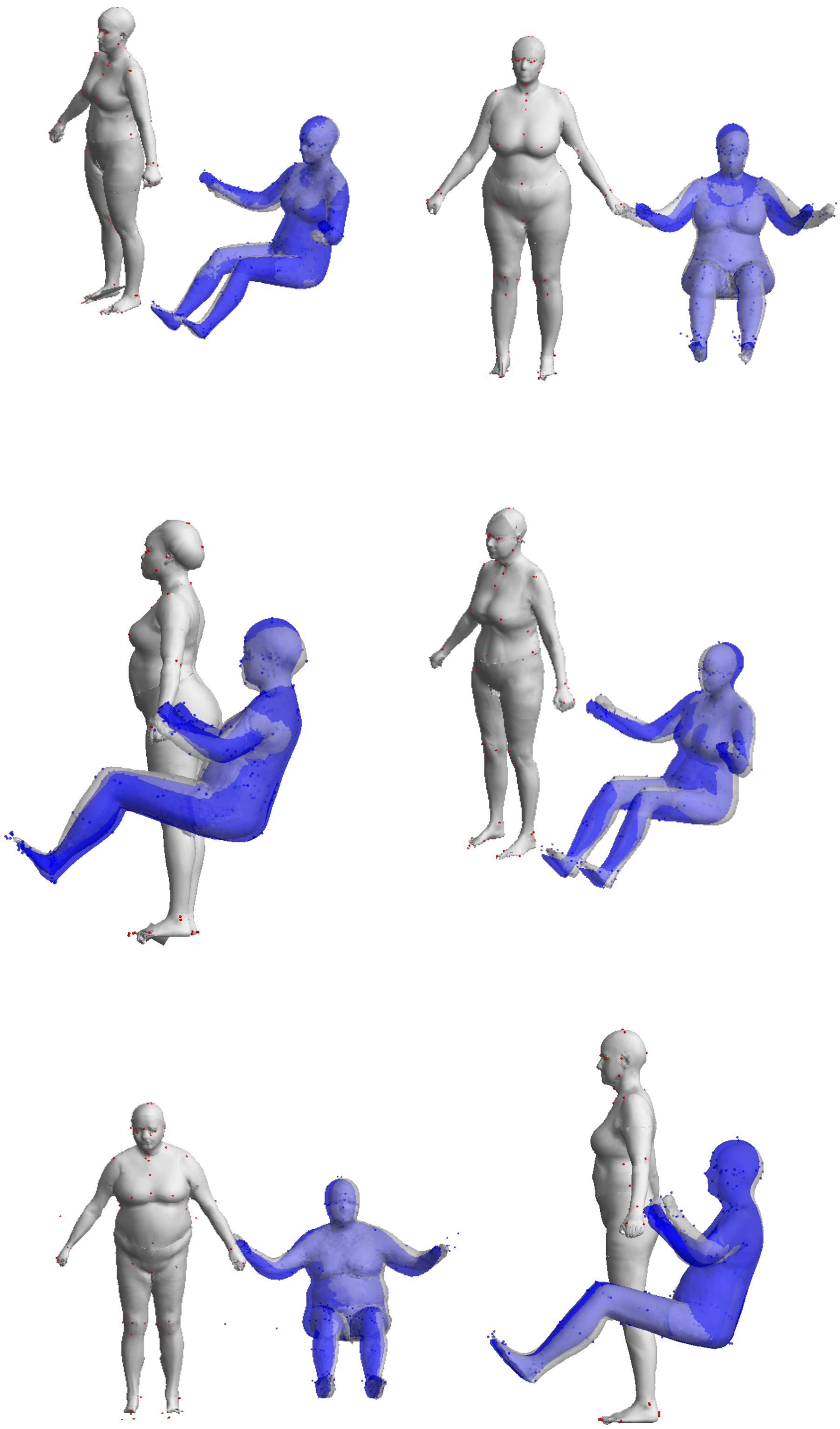

Figure 3. Comparison of measured and predicted seated body shapes. In each case, the template-fitted scans are shown in gray, the predicted seated body shape in blue.

4. Discussion

To our knowledge, this is the first published description of this method, but the approach is sufficiently simple that other researchers may have used it in the past. Nonetheless, the method is quite powerful, because it can be applied quite broadly and in a variety of contexts. For example, Hu et al. (2013) presented a method for assessing automobile seatback shape using seated body shapes. Using the current methods, these shapes can be generated from a dataset containing standing postures but lacking supported seated postures, such as CAESAR (Reed et al. 2008). The method can also be used to predict difficult-to-measure supported seated postures from standing postures that can be easily recorded using low-cost depth cameras (Park and Reed (2014).

The method is limited in that a relatively large amount of high quality body scan data is needed in each of the postures for which predictions are desired. Moreover, template fits must be performed in each posture so that a PCA can be conducted. In principal, the prediction could be performed directly on the vertex coordinates with no loss of fidelity, but in practice it is more efficient to predict PC scores.

The number of scans from the target population that are needed is fairly small. We've found that adding scans beyond about 120 does not meaningfully improve the model performance, even in the tails of the anthropometric distribution, because the models are inherently linear. Consequently, there is also no risk of overfitting.

The most important limitation is that the model predictions are based on the particular population of individuals who are scanned. If the body shape of the target individual lies within the scanned population, then the predictions should be quite accurate. The current model is based on an anthropometrically diverse population and appears to perform well for a wide range of body types, but more work is needed to assess the quality of the predictions for markedly different populations. It would not be expected to work well for a population with different origin from the source data, such as East Asian or African.

A second limitation is that the predictions of alternative postures are not based on a specific kinematic linkage, and hence the only postures that can be generated by this procedure are those with available scan data. However, if the target posture is close to the posture that is desired for a particular ergonomic analysis, this limitation becomes a strength, because it is not necessary for the model to have blending functions enabling such a large posture change. This might be valuable for initializing new baseline body shapes for different seated conditions. Moreover, we have previously demonstrated methods for driving posture change for seated body shapes using surface landmark configurations (Reed 2013), which are available from posture-prediction models, such as Park et al. (2015).

5. Conclusion

This paper demonstrated a straightforward method for predicting seated body shapes from standing data. Applications include vehicle seat design and vehicle interior layout.

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