Creating a Personalized Full 3D Body Shape from a Limited Number of Predictors

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Abstract. The use of statistical body shape models (SBSM) offers the possibility to generate a realistic full body shape with a limited number of measures/predictors such as traditional anthropometric dimensions, surface landmarks etc. The purpose of the present work is to explore the possibility to create a personalized surface model with a small set of easily measurable parameters, and to compare the quality of SBSM-based prediction in function of predictors. A sample of 164 full body scans in a standing posture from European and Chinese males were selected based on stature and BMI. After cleaning the raw scans, a non-rigid mesh deformation method was used to fit a customized template onto scans. Then, a principal component analysis (PCA) was performed to build SBSM with different set of predictors, including anthropometric dimensions, landmarks' coordinates, postural parameters. The partial least square regression was used to take into account correlated nature between predictors. As statistical models cannot match the target values of predictors, an optimization was further proposed for better matching targets while not deviating too much from the initial prediction by statistical regression. A leave-one-out (LOO) procedure was used to evaluate the quality of SBSM with different set of predictors.

Keywords. 3D statistical shape model, human body shape, PCA, anthropometry

1. Introduction

An accurate and personalized full 3D body shape in a position of interest is needed for many applications such as textile industry for specifying product size. In postural and motion analysis, researchers often need to define a subject specific digital human model to understand the interaction between a person and environment [1]. Though a full body surface can be easily scanned using a body scanner, raw scans are generally noisy, incomplete, and require a more or less time consuming post processing to obtain a workable surface model [2]. In recent years, thanks to the development of statistical body shape models (SBSM) [3], researchers used these models to remove noise, complete holes making it possible to create high quality surface models from a low cost depth camera [4] or even from a single image [5]. The use of SBSM also offers the possibility to generate a realistic full body shape with a limited number of measures/predictors such as traditional anthropometric dimensions, surface landmarks etc. Though parametric human body modelling approaches (see for example [6]) have been developed for many years, a systematic evaluation of prediction accuracy in function of predictors is missing. The purpose of the present work is to explore the possibility to create a personalized

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surface model with a small number of easily measurable parameters, and to compare the quality of SBSM-based prediction in function of predictors.

2. Materials and method

2.1. Scan data and processing

A sample of 164 full body scans of European and Chinese males in a standing posture from an existing database of Decathlon SportsLab were selected based on stature and BMI (**Table 1**). After cleaning the raw scans, a non-rigid mesh deformation method was used to fit a customized template onto scans using mHBM [7]. An experienced researcher identified 27 landmarks manually on the body surface by virtual palpation (**Figure 1**). They were used for template fitting. An example is shown in **Figure 2**. Due to artefacts (e.g. hair) and insufficient scan quality, head mesh was re-adjusted according to the head height manually measured at the same time as 3D body scanning, which is defined as the vertical distance from the bottom of the chin to the top of the head.

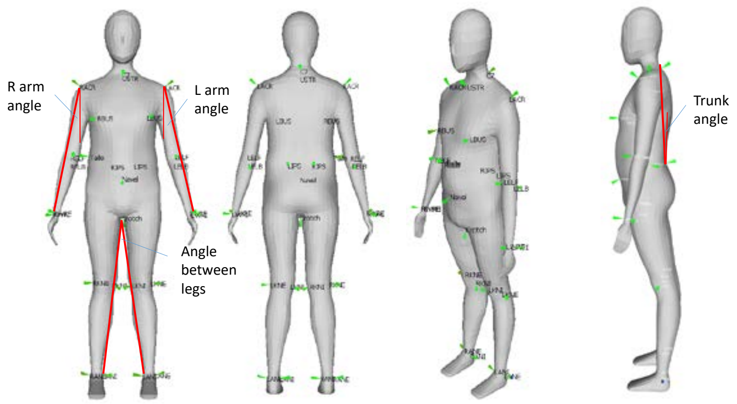

Figure 1 Customized template and landmarks. Four postural angles are also illustrated.

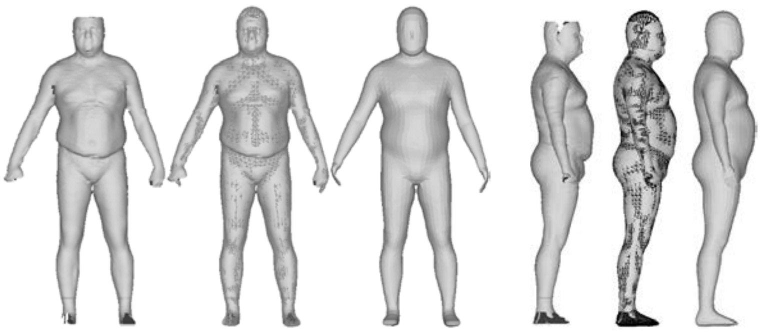

Figure 2 An example showing a raw scan and mesh after template fitting

Table 1. Summary of the statistics of stature, weight and BMI of selected European and Chinese males

	Europe			China		
	Stature (mm)	**Weight (kg)**	**BMI (kg/m²)**	**Stature (mm)**	**Weight (kg)**	**BMI (kg/m²)**
N	83	83	83	81	81	81
Average	1744.2	80.3614	26.3973	1723.5	78.9	26.6
Standard deviation	58.46	12.4583	3.79265	74.2661	15.9	4.98
Coeff. of variation	3.35%	15.50%	14.37%	4.31%	20.13%	18.73%
Minimum	1617.3	57.0	18.3	1537.1	53.2	18.3
Maximum	1895.3	134.0	43.8	1871.7	119.0	41.0
Range	278	77.0	25.5127	334.62	65.8	22.7

2.2. Anthropometric and postural parameters

For each scan, a homologous model was created by template fitting, from which 18 anthropometric dimensions were extracted:

- 4 heights: stature, crotch height, C7 height, knee height
- 3 lengths: upper arm length, forearm length, total arm length
- 11 circumferences: at hip, waist, chest, knee, ankle, elbow; thigh circumferences at crotch and middle of thigh, circumferences of lower leg, upper arm and forearm at their middle

To reduce data variability due to postural variation, four postural parameters were extracted with help of pre-defined landmarks (**Figure 1**):

- Trunk angle: angle between the vertical and the mid IPS (middle between left and right posterior superior iliac spines) to C7 line
- Right and left arm angle: angle between the vertical and the acromion to wrist line
- Angle between legs: angle formed by left internal ankle point, crotch and right ankle point.

2.3. PCA models

All registered scans were at first aligned using the palpated surface landmarks. The 3D coordinates of vertices from *n* subjects were put in a matrix Ψ_{n*r}, with *r* being 3*number of vertices (variables). The *s* (=3*27) coordinates of the 27 landmarks were appended to Ψ_{n*r} resulting in a matrix $\Psi_{n*(r+s)}$. A smaller set of ordered variables, called principal component (PC) scores, was obtained with a principal component analysis (PCA), so that the first PCs retained most of the variation in data. PC scores were calculated for each subject. An intuitive interpretation of the PCs can be performed by varying the scores along each component from (mean -2SD) to (mean +2SD).

From the PCA of $\boldsymbol{\Psi}$, assume that *m* main PCs $\mathbf{u}_j$ (j=1, *m*) are retained. The vertex coordinates of a body shape $\mathbf{v}_{(r+s)}$ can be approximated:

$$\mathbf{v} \approx \bar{\boldsymbol{\mu}} + \sum_{j=1}^{m} y_j \boldsymbol{u}_j \qquad (1)$$

where $\bar{\boldsymbol{\mu}}$ is the average from the sample data sets Ψ and y_j is the unknown score associated with j^{th} PC. The m unknown scores $\mathbf{y}$ ($y_1, y_2, \ldots y_m$) can be estimated by statistical regression, optimization or a combination of both. In the present work, *m* was chosen for accounting for 99.5% of data variance.

2.4. PLS Statistical regression

To estimate of a new body shape from p predictors $x_1, x_2, \ldots x_p$ such as stature, crotch height, waist circumference, etc, the problem now is to estimate *m* unknown scores $y_1, y_2, \ldots y_m$. As predictors such as anthropometric dimensions are generally correlated, the partial least (PLS) regression is a good technique. As for multiple linear regression, PLS regression takes the same form with the model parameters $\beta_{j,k}$ which relates *p* predictors $x_k, k = 1, p$ with for *m* PC scores $y_j, j = 1, m$. The predictors are not limited to anthropometric dimensions. They can be postural variables as well as landmarks.

2.5. Optimisation

Once statistical shape models (SSMs) obtained by PLS regression, they can be used to predict a full body shape using a small number of predictors. An optimization procedure is proposed to find the PC scores **y** to better match target predictors while not too much deviating the prediction by SSM. The objective function is defined as

$$f(y_1, y_2, \ldots y_m) = \rho_1 \left(\frac{1}{p_1}\sum_{i=1}^{p_1}\left(x_{ai}^{target} - x_{ai}^{current}\right)^2\right) + \rho_2 \left(\frac{(H/4)^2}{p_2}\sum_{i=1}^{p_2}\left(x_{pi}^{target} - x_{pi}^{current}\right)^2\right) + (1 - \rho_1 - \rho_2)\left(\frac{1}{v}\sum_{j=1}^{v}\|\boldsymbol{v}_j^{current} - \boldsymbol{v}_j^{ssm}\|^2\right) \quad (2)$$

While x_{ai}^{target}, x_{pi}^{target}, $x_{ai}^{current}$, $x_{pi}^{current}$ are i^{th} target and current anthropometric and postural predictor values, $\boldsymbol{v}_j^{current}$, $\boldsymbol{v}_j^{ssm}$ are j^{th} vertex of the current mesh and one predicted by SSM. p_1 and p_2 are number of anthropometric and postural predictors. H is stature. Multiplying the differences between target and current postural angles by H/4 to is to convert postural difference in distance for facilitating the definition of weighting coefficients ρ_1 and ρ_2. In the present work, they were fixed as $\rho_1 = 0.5$, $\rho_2 = 0.3$.

When landmarks are used as predictors, we prefer using the optimization algorithm proposed by Rajamani et al. [8] for reason of efficiency in calculation. PC scores are found by minimizing the distance between target and current landmarks while not too much deviating the mean body shape $\bar{\boldsymbol{\mu}}$.

2.6. Leave-one-out cross validation

Four methods of prediction based on predictors were tested:

1. Stature, Crotch height, Waist circumference, 5 postural angles
2. 1 + Hip circumference + Chest circumference
3. 2 + Arm length + Thigh circumference + Upper arm circumference

4. 27 landmarks

To reduce the body shape variability due to postural change, all five postural parameters were used as predictors for the first three methods.

For each set of predictors, a leave-one-out (LOO) cross validation was performed. For each scan, its data was used to define the predictors, while the rest of scans were used to build SSM. Predicted shapes were aligned with the original one using 27 landmarks. The predictions by optimization were compared with the original body shape model after template fitting. The following parameters are calculated:

- Root mean square errors in the predictors used as targets (RMS_pr)
- Root mean square errors in 18 anthropometric dimensions (RMS_an)
- Root mean square distances between predicted and original vertices for the whole body (RMS_wb)
- Root mean square distances between predicted 27 landmarks and original ones (RMS_lm), which is equal to RMS_pr for Method 4.

3. Results

656 simulations (164 subjects x 4 sets of predictors) were performed for LOO validation. Means and standard deviations for RMS_pr, RMS_an, RMS_wb and RMS_lm are summarized in **Table 2**. Concerning the error between target and predicted parameters, RMS_pr was all lower than 4 mm on average. For anthropometric dimensions, significant differences in RMS_an between four methods of prediction were observed. Method 3 had the lowest error, while Method 4 obtained the lowest error for whole body vertices and landmarks. Comparing three first methods, lower error in anthropometric parameters was observed when increasing the number of anthropometric predictors. Using 27 landmarks as predictors, the errors in whole body vertices could be highly reduced (lower than 10 mm on average). However, the error in anthropometric dimensions was not reduced as much as for vertices.

Table 2. Means and standard deviations (in mm) of the root mean square errors in the predictors (RMS_pr) and all 18 extracted anthropometric dimensions (RMS_an), root mean square distances between predicted and original vertices (RMS_wb) for the whole body and between predicted 27 landmarks and original ones (RMS_lm) for four sets of predictors.

Method	RMS_pr		RMS_an		RMS_wb		RMS_lm	
1	1.87	±1.15	22.67	±7.45	21.20	±5.46	22.47	±6.29
2	2.73	±1.38	17.67	±5.25	21.29	±5.33	22.64	±6.05
3	2.41	±1.63	14.76	±4.86	21.94	±5.58	23.26	±6.29
4	3.92	±0.54	19.13	±6.28	9.75	±2.11	3.92	±0.54

4. Discussion

In the present work, we have developed PCA based statistical body shape models (SBSM) from 164 European and Chinese males and implemented two optimization algorithms to find PC scores to better match target predictors while preserving the body shape predicted by SBSM. Four methods by predictors were compared by LOO cross validation.

Results are in agreement with *a priori* expectations. More anthropometric predictors resulted in lower errors in extracted anthropometric dimensions. Compared to Method 1 with three anthropometric dimensions as targets (stature, crotch height and waist circumference), five additional anthropometric targets (arm length, circumferences at the hip and chest, thigh and upper arm circumference) reduced the error in 18 extracted anthropometric dimensions by 35% (from 23 to 15mm on average). However, no significant differences in RMS_wb and RMS_lm were found between three first methods. This is probably because body shape error is much more dependent on posture than error in anthropometric dimensions, and five postural angles used in this work could not fully describe the body shape variation due to postural change between different subjects. **Figure 3** shows the predictions by 4 methods for two subjects, one with lower prediction errors in both anthropometric dimensions and body shape, and one with larger errors. Higher errors for the second subject are mainly due to postural difference, especially for the arms.

Method 4 used 27 body landmarks as targets. Less than 10 mm on average in root mean square distances between predicted and original mesh vertices was obtained, much lower than the predictions by the first three methods. However, the error in anthropometric dimensions was higher than the error by Method 3. The 27 landmarks were mainly selected to define internal joint centers. Apart from three landmarks (navel, right and left nipples), all others correspond to bony landmarks. From **Figure 3**, one can see that Method 4 could predict a body shape with good posture. However, as no landmarks could provide the information about the circumferences of four members, the error in anthropometric dimensions was not much reduced. To further improve the prediction; additional landmarks should be added providing the information about the circumferences of different body segments. We should note that landmarks were virtually palpated on raw scans. Palpation may not be repeatable and there may be large inter-operator even intra palpation variability.

The distances between predicted and original vertices for the whole body (RMS_wb) provide a valuable metric for assessing different prediction methods. The node-to-node distance overestimates the distance between surfaces. A node-to-surface distance could be more relevant and could be considered in the future.

As prediction error depends on the choice of predictors, depending on application, a minimum number of predictors should be determined. One can for example refer to ISO 20685-1 [9] to define the maximum allowable error between predicted and scan extracted values.

In summary, combining a statistical body shape model (SBSM) and an optimization procedure can predict a subject-specific whole body shape with a small number of predictors. Prediction accuracy depends on number of predictors. With only three anthropometric dimensions (stature, crotch height and waist circumference), we observed the root mean square errors in both anthropometric dimensions and whole body shape less than 23 mm. Prediction error could be further reduced by using more postural parameters. We are planning to create a full articulated skeleton with help of bony landmarks and calculate corresponding joint angles. Surface markers attached on the body are usually used for motion and postural analysis. Our results show that it is possible to generate an accurate whole body surface from these landmarks. To improve prediction accuracy, non-bony landmarks should be added to provide information about segment size.

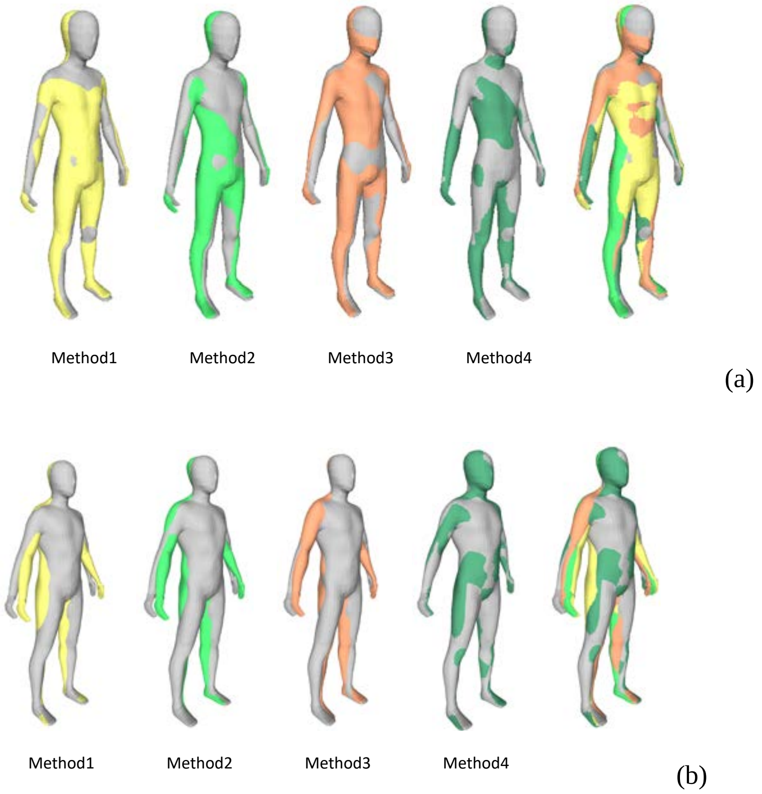

Figure 3. Illustration of the body shapes predicted by four different methods for two subjects. From left to right, predictions by Method 1 to 4 are superimposed with the original model after template fitting. (a) A subject with smaller errors in both anthropometric dimensions and whole body shape with RMS_an=9.1mm, RMS_wb=18.8mm for Method 3. (b) A subject with larger prediction errors with RMS_an=20mm, RMS_wb=33mm for Method 3.

References

[1] Wang X., Chevalot N., Monnier G., Ausejo S., Suescun Á., Celigüeta J. Validation of a model-based motion reconstruction method developed in the Realman project. SAE 2005 International conference and exposition of Digital Human Modeling for Design and Engineering, Iowa city, IA, Etats-Unis, 14–16 juin 2005, SAE Paper 2005–01–2743 (2005)

[2] Shu C., Wuhrer, S., Xi P. 3D anthropometric data processing. Int. J. of Human Factors Modeling and Simulation, vol. 3, no2, p. 133-146 (2012)

[3] Allen B., Curless B., Popovic Z. The space of all body shapes: reconstruction and parameterization from range scans. ACM Transactions on Graphics (ACM SIGGRAPH 2003), 22, 3, 587-594

[4] Park B.K., Lumeng J.C., Lumeng C.N., Ebert S.M., Reed M.P. Child body shape measurement using depth cameras and a statistical body shape model, Ergonomics, 58:2, 301-309 (2015), DOI: 10.1080/00140139.2014.965754

[5] Bogo F., Kanazawa A., Lassner C., Gehler P., Romero J., Black, M.J. Keep it SMPL: Automatic Estimation of 3D Human Pose and Shape from a Single Image. arXiv:1607.08128 [cs], 27 July 2016. http://arxiv.org/abs/1607.08128.

[6] Baek S. Y., Lee K. Parametric Human Body Shape Modeling Framework for Human-Centered Product Design. Computer-Aided Design, Digital Human Modeling in Product Design, 44, no 1 (1 janvier 2012): 56-67. https://doi.org/10.1016/j.cad.2010.12.006.

[7] Yamazaki S., Kouchi M., Mochimaru, M. Markerless landmark localization on human body scans by non-rigid model fitting. Proceedings of the 2nd International Symposium on digital human modelling, Ann Arbor, Michigan, USA, June 11-14, 2013.

[8] Rajamani K, Styner M, Talib H, Zheng G, Nolte L, Ballester M. Statistical deformable bone models for robust 3D surface extrapolation from sparse data. Medical Image Analysis. 2007;11(2):99-109

[9] NF EN ISO 20685-1:2018. 3-D scanning methodologies for internationally compatible anthropometric databases - Part 1 : evaluation protocol for body dimensions extracted from 3-D body scans. CEN-CENELEC Management Centre: Rue de la Science 23, B-1040 Brussels