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Using 3D Statistical Shape Models for Designing Smart Clothing

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Abstract. In this paper we present an innovative approach to design smart clothing using statistical body shape modeling (SBSM) from the CAESAR™ dataset. A combination of different digital technologies and applications are used to create a common co-design workflow for garment design. User and apparel product design and developers can get personalized prediction of cloth sizing, fitting and aesthetics.

Keywords: Statistical body shape modeling (SBSM) · Anthropometry Blender · Motion capture · Smart clothing

1 Introduction

Statistical shape modeling is a promising approach to map out the variability of body shapes, commonly used in 3D anthropometric analyses. With statistical shape models, a wide range of body shapes can be simulated. So, a wide range of 3D smart garment can be designed on it as well.

The design of smart clothing is crucial to obtain the best results. Identifying all the steps involved in the functional design workflow can prevent a decrease in the wearer's performance ensuring a successful design [1–5].

Nowadays, smart clothing provides a methodology to monitor mechanical, environmental, and physiological parameters in real time and in an ecological, non-intrusive approach. These parameters can be used to detect gesture or specific patterns in movement, design more efficient, specific training programs for performance optimization, and screen for a potential causes of injury.

Apparel sizing and fit impact every part of the apparel lifecycle, from design to manufacturing to the consumers. The main requirements that a smart clothing is called to achieve are functionality, usability, monitoring duration, wearability, maintainability, connectivity and washability [6]. On the other hand comfort is a fundamental and a

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transversal factor (also among the previous features) that has to be considered. Wearing an uncomfortable system comprises the user's ability to do his/her job.

Anthropometry is a key for the clothing design and the placement of smart textiles around the body. Volume, shape, weight, and adherence to the body of wearable devices must be designed to not affect or interfere with natural movements. Statistical body shape modeling (SBSM) can allow mapping out the variability of the shape of the clothes, thus contributing to more successfully sized and better fitting apparel (Fig. 1).

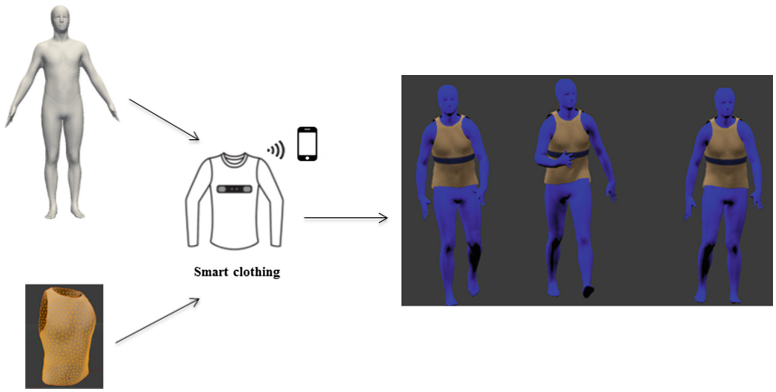

Fig. 1. SBSM for design smart clothing.

The innovative approach we propose, concerns a combination of different digital technologies and applications to create a common co-design workflow for the design of a garment [7]. Users or designers could upload the SBSM and get a personalized prediction of clothing size as well as personalized suggestions on how different products may fit their body enhancing performance and functionality [8].

In our case, the SBSM was built selecting 57 soldiers-like body shapes from the CAESAR™ database to design smart clothing for this specific military population.

2 Methods

In this section, the method for building an SBSM for designing smart clothing is described. First, a moving SBSM is built from 3D human body scans. Human activities can then be replicated based on body shape and a motion data collected on a subject by a mocap system. This provides a visualization of a digital human model based upon anthropometry and biomechanics of the subject [9]. Furthermore, an SBSM garment for a specific body shape can then be created. The rigging phase allows visualizing the garment fitting and aesthetics [10]. A clustering algorithm can finally be used to determine a sizing systems based on the biometric features of the subject [11, 12].

2.1 Building a Statistical Body Shape Model

First, a digitally modeled body shape with n uniformly distributed vertices is registered in a marker-less way to all input surfaces to obtain a homologous point-to-point correspondence. All input surfaces were corrected for posture, in a way that every shape was standing in the average posture. Then, a statistical shape model is built using principal component analysis on the corresponded surfaces [13, 14]. We selected 57 soldiers body shapes (male, height 1520 mm–2100 mm, age 18y–35y, BMI < 25) from the CAESAR™ database [15] to build our model. In this statistical shape model, the average shape $\bar{\boldsymbol{x}}$ and the main shape modes, or the principal component (PC) modes of the shape model $\boldsymbol{P}$, are incorporated (Fig. 2). This means that a new shape $\boldsymbol{y}$ can be formed by a linear combination of the PCs:

$$\boldsymbol{y} = \bar{\boldsymbol{x}} + \boldsymbol{Pb} \tag{1}$$

with $\boldsymbol{b}$ the vector containing the shape parameters of a specific instance.

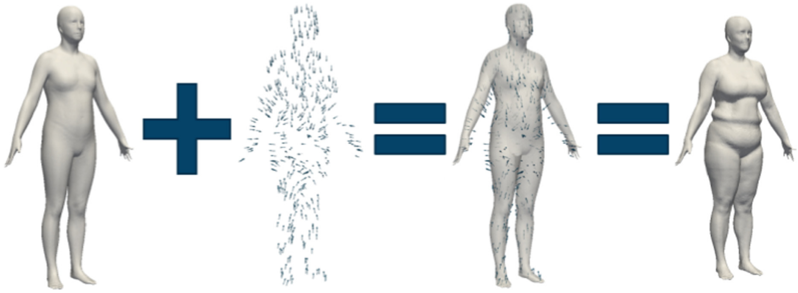

Fig. 2. Example of generating a new body shape with specific shape parameters. The average body shape $\bar{\boldsymbol{x}}$ is added to the shape $\boldsymbol{Pb}$. The result is the average body with a displacement vector for each vertex. When the displacement is applied to the shape, a new body shape is formed.

A mapping matrix $\boldsymbol{M}$ describing the relationship between the biometric features $\boldsymbol{F}$ (such as height, weight, gender,…) and the principal component weights matrix $\boldsymbol{B}$ of every input shape was calculated using multivariate regression, by $\boldsymbol{M} = \boldsymbol{BF}^+$ with $\boldsymbol{F}^+$ the pseudoinverse of $\boldsymbol{F}$. By multiplying $\boldsymbol{M}$ with a given feature vector $\mathbf{f}$, new PC weights can be generated: $\boldsymbol{b} = \boldsymbol{Mf}$. From these PC weights, a new body shape can be built.

2.2 Generating a Shirt

On this new body shape, a shirt is designed. This is done by calculating critical points. The root of the hips, neck, left shoulder and right shoulder were calculated. Then, a clipping plane was generated on every critical point with a pre-defined normal. For the hips, this normal was defined as $(0, 0, 1)$. The normal for the neck was $(0, 0.707, -1)$. The left shoulder plane had as normal $(-1, -0.2, 0)$, and the right shoulder had

$(1, -0.2, 0)$. After removing the arms, legs and head of the body shape, it was scaled by a scaling matrix $\boldsymbol{S}$ with the origin at $(0, 0, 0)$.

$$\boldsymbol{S} = \begin{bmatrix} 1.1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1.1 \end{bmatrix} \tag{2}$$

The shirt was uniformly resampled to 1000 points. The body mesh and the cloth were exported as object files.

2.3 Clustering

The surfaces are clustered by PC weights, using the k-means clustering algorithm of Hartigan and Wong [16]. K-means clustering aims to partition N observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. The goal is to minimize the within-cluster sum of squares:

$$\sum\nolimits_{j=1}^{k} \sum\nolimits_{i=1}^{N} \left\| \boldsymbol{x}_i - \boldsymbol{\mu}_j \right\| \tag{3}$$

with $\boldsymbol{x}_i$ the vector holding the parameter weight vectors of a specific surface and, $\boldsymbol{\mu}_j$ the average parameter weight vector of the set. In this case the N observations are the parameter weight vectors per surface. Finally, the characteristic shape per cluster was returned.

3 Experiment and Results

3.1 Combined Techniques (3D to 2D and 2D to 3D)

The co-design workflow (Fig. 3) was implemented in Blender [17]. Blender as an open source 3D computer graphic software can be used to rig the mesh cloth with an SBSM describing all the phases necessary to simulate garment fitting and aesthetics [18]. First, a moving SBSM was built from a population of 3D human body shapes (Fig. 2). Next, the garment shape and sizing system was created (Fig. 4). The following step involves importing the file in Blender as an object file (OBJ). After that, the UV mapping followed (Figs. 5 and 6). Finally there was the rigging phase where the cloth mesh was rigged to the humanoid mesh (Figs. 7 and 8).

3.1.1 Creating Mesh

A shirt was created for a specifically generated body shape, by cutting the surface on predefined locations (arms, legs, neck) and scaling the surface. The resulting shirt was shown in Fig. 4.

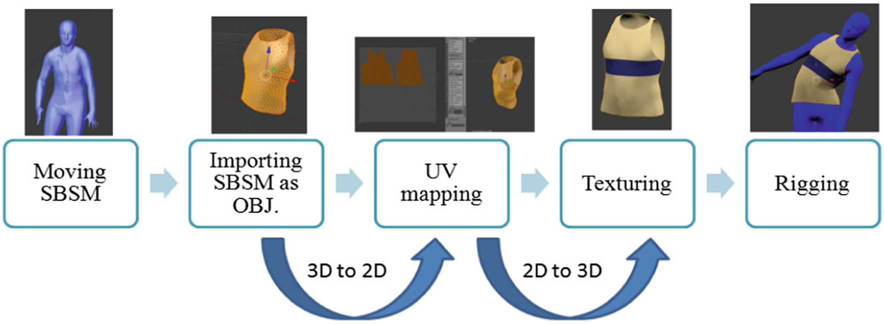

Fig. 3. Garment co-design workflow in Blender.

Fig. 4. The generated shirt (left-frontal view) and (right-sagittal view).

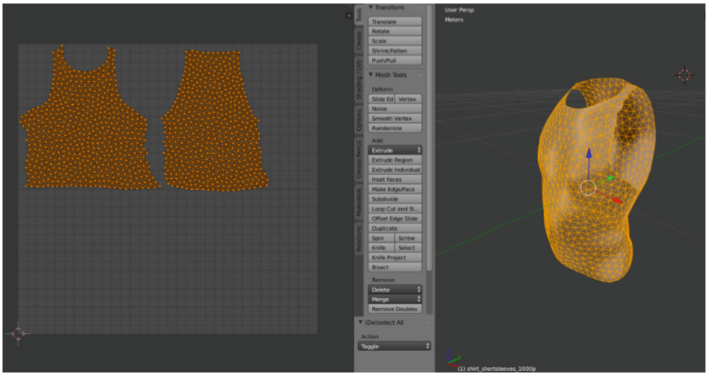

Fig. 5. UV's unwrapped (on the left) and UV mapping (on the right) in Blender.

3.1.2 UV-Mapping Your Meshes

UV mapping is the process of projecting the 3D surface onto a 2D texture surface [19]. Each face of the 3D model is mapped to a face of the UV map. Each face on the UV map corresponds to one face of the 3D model, and the UV preserves the edge relationships between faces of the 3D model.

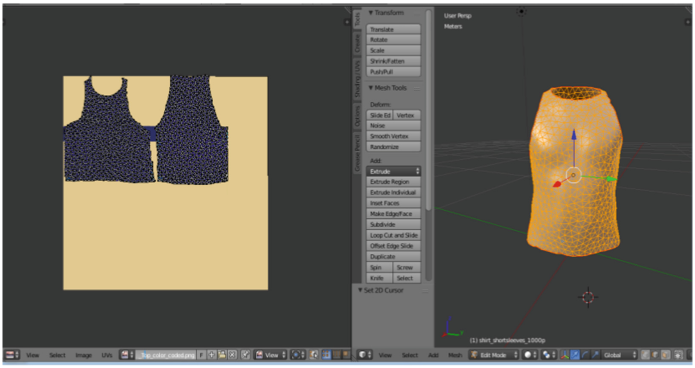

Fig. 6. UV's unwrapped (on the left) with the texture and UV mapping (on the right) in Blender.

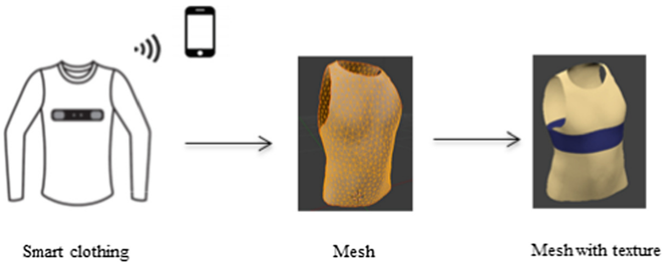

Fig. 7. Smart clothing texturing.

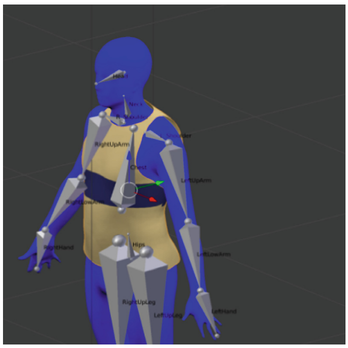

Fig. 8. The skeleton parented with the humanoid and clothing meshes.

The UV mapping process requires three steps: unwrapping the mesh (Fig. 5), creating the texture and applying the texture. Texturing is a process where an image is applied (mapped) to the surface of a shape or polygon (Fig. 6). In our case a texture representing the aesthetics of the cloth was mapped on the cloth mesh (Fig. 7).

3.1.3 Rigging

Rigging [17] refers to a process in which the mesh is attached to the skeleton (Fig. 8) associating a movement to a BVH file [20] (Fig. 9).

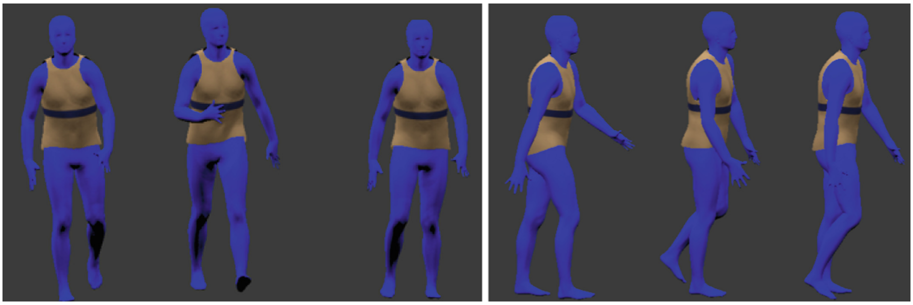

Fig. 9. Moving SBSM with clothing in Blender (left-frontal view and right-sagittal view).

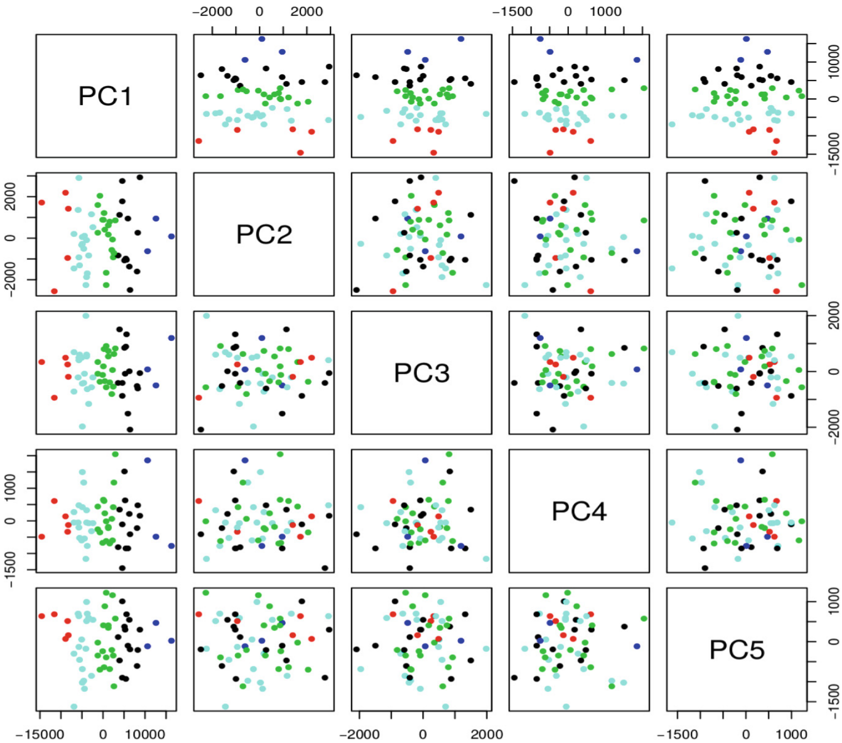

Fig. 10. Plot of the clusters in the PCA space. The clusters are shown by the same color. The red dots belong to cluster 1 (Small), the cyan dots to cluster 2 (Medium), the green dots to cluster 3 (Large), the black dots to cluster 4 (X-Large), and the blue dots to cluster 5 (XX-Large). The average shape per cluster is shown in Fig. 11. (Color figure online)

3.2 Clustering

The 57 body shapes were subjected to the clustering algorithm. In our experiments, the number of initial clusters was set to five, since that corresponds to the number of clothing sizes (Small, Medium, Large, X-Large and XX-Large) we were interested in identifying (Fig. 10). As can be seen from the results, the main difference between the clusters was the height. The body shapes that correspond to these measurements are shown in Fig. 11. Table 1 shows a subset of the body measure and standard deviation of the average shape of each cluster in mm.

For smart shirt design, the anthropometric cluster, gave an indication of the size constraints of an individual. While, moving SBSM was used to modify the aesthetics design and garment fitting.

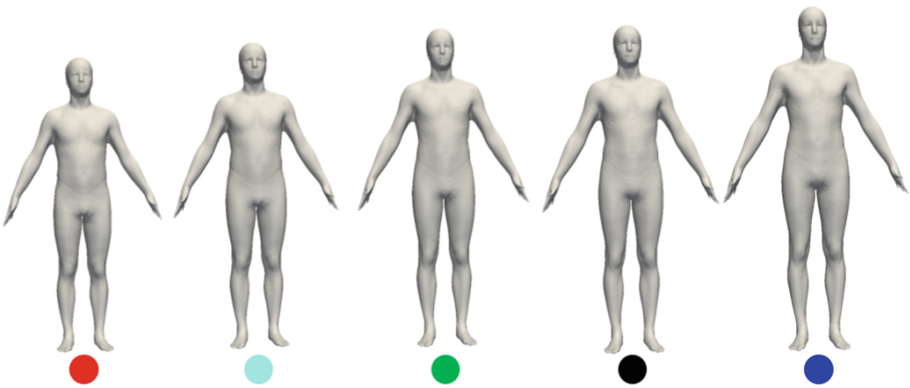

Fig. 11. Average shape of every cluster. Red: 1725 mm, 63.6 kg (Small), Cyan: 1787 mm, 72.4 kg (Medium), Green: 1856 mm, 77.1 kg (Large), Black: 1913 mm, 82.2 kg (X-Large) and Blue: 2000 mm, 91.3 kg (XX-Large). (Color figure online)

Table 1. Body measurements (mean values are given in mm along with the standard deviation in parenthesis).

Parameter	Small	Medium	Large	X-Large	XX-Large
Shoulder to wrist	603 (26)	631 (16)	652 (20)	689 (21)	721 (51)
Chest circumference	902 (84)	942 (50)	940 (37)	979 (58)	1009 (41)
Bust chest circumference under bust	902 (84)	942 (50)	940 (37)	972 (61)	1009 (41)
Hip circumference	907 (60)	984 (42)	992 (39)	1007 (48)	1059 (52)
Shoulder breadth	449 (24)	453 (16)	470 (19)	474 (18)	503 (11)
Sitting height	915 (13)	927 (24)	958 (25)	977 (28)	1012 (20)

(*continued*)

Table 1. (*continued*)

Parameter	Small	Medium	Large	X-Large	XX-Large
Stature	1725 (31)	1787 (19)	1855 (15)	1912 (21)	2000 (34)
Waist circumference	793 (55)	841 (46)	828 (53)	880 (66)	889 (47)

4 Conclusion

This study demonstrates a co-design approach to smart clothing development using moving statistical body shape models. This methodology can be applied to apparel design ensuring a more successful design. The advantage of using an SBSM is that our method can be applied to a whole range of body shapes, e.g. specific shape clusters that correspond to a specific size. Anthropometric soldier dimensions can be used to design ergonomic military equipment and functional clothing.

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