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Automatic Generation of Statistical Shape Models in Motion

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Abstract. Statistical body shape modeling (SBSM) is a well-known technique to map out the variability of body shapes and is commonly used in 3D anthropometric analyses. In this paper, a new approach to integrate movement acquired by a motion capture system with a body shape is proposed. This was done by selecting landmarks on a body shape model, and predicting a body shape based on features. Then, a virtual skeleton was generated relative to those landmarks. This skeleton was parented to a body shape, allowing to modify its pose and to add pre-recorded motion to different body shapes in a realistic way.

Keywords: Statistical body shape model · Motion capturing · Shape prediction

1 Introduction

Statistical body shape modeling (SBSM) is a well-known technique to map out the variability of body shapes and is commonly used in 3D anthropometric analyses. Statistical body shape models (SBSMs) can describe the variability of body shapes for a population of individuals. By adapting the parameters of the SBSM, a new realistic shape can be formed. Product developers may exploit SBSMs to design virtual design mannequins and explore the body shapes belonging to a specific percentile of a target group, allowing to visualize extreme shapes. Moreover, an SBSM allows to simulate a specific 3D body shape [1], which is useful for customization.

Nowadays, inertial motion tracking sensors (IMU) allow capturing human motion and acquiring the kinematic of the subject during a physical task. This information is translated as a skeletal animation as a Biovision Hierarchy (BVH) character animation file. In this study, we acquired the subject's motions with a real-time inertial motion tracking system (Yost Labs 3-Space Sensor).

This is especially relevant for people who have to perform physically demanding tasks in non-ideal circumstances. Their gear must have an optimal fit, to reduce the

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impact on their body. For example, reachability tests in vehicles or testing the freedom of movement when wearing their equipment or heavy backpacks [2, 3].

Unfortunately, to date, there is no framework available to generate body shapes in motion where both body shape as articulation is adaptable. Another possibility is to add motion to a specific body scan. We propose a new approach to integrate the movement acquired by an inertial motion capture system with the statistical body shape. This allows product developers to validate their designs for multiple poses and movements.

2 Methods

In this section, a framework to create moving SBSMs is described. First, a SBSM is built from a population of 3D human body shapes [4]. Next, the method to generate a body shape based on features is explained [1]. Finally, modification of a motion file and adding motion to a specific body shape is discussed.

2.1 Building a Statistical Shape Model

First, a reference surface, a digitally modeled body shape [5] with n uniformly distributed vertices, is registered in a marker-less way to N 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, determined from a population of 700 scans from the CAESAR database [4]. Then, a statistical shape model is built using principal component analysis of the population of N posture normalized corresponded surfaces. In an SBSM, the mean shape $\bar{x} \in \mathbb{R}^{3n}$ and the main shape modes, or the principal component (PC) modes of the SBSM $P \in \mathbb{R}^{3n \times (N-1)}$, are incorporated. This means that a new shape $y \in \mathbb{R}^{3n}$ can be formed by a linear combination of the PCs:

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

with b the vector containing the SBSM parameters.

A specific feature of a person's shape, such as height, can be adapted by adding a linear combination of principal components to the person's shape vector. The weights for this linear combination are computed via multiple linear regression of the PC weights on the body features $f = \left[f_1 f_2 f_3 \cdots f_f\ 1\right]^T \in \mathbb{R}^{f+1}$ (such as height, weight, gender,…) for the population of individuals. Every feature is defined by a scalar value. A mapping matrix $M \in \mathbb{R}^{N-1 \times (f+1)}$ describing the relationship between the biometric features $F = [f_1 f_2 f_3 \cdots f_N] \in \mathbb{R}^{(f+1) \times N}$ of every input shape and the principal component weights of every input shape $B \in \mathbb{R}^{(N-1) \times N}$ is calculated using multivariate regression, by

$$M = BF^+, \tag{2}$$

with F^+ the pseudoinverse of F.

By multiplying M with a given feature vector f, new principal component weights $b \in \mathbb{R}^{N-1}$ can be generated:

$$b = Mf. \tag{3}$$

From these principal component weights, a new body shape $\boldsymbol{y}$ can be built.

2.2 Skeleton Generation

The BHV file format is a way to provide skeleton hierarchy information in addition to the motion data. The skeleton is typically in T-pose. In such a BVH file, the skeleton is represented as a tree structure set of 18 joints, relative to each other. This is shown in Fig. 1. In most cases, the pelvis is the root of the skeleton. Every other joint is defined by an offset from the previous joint.

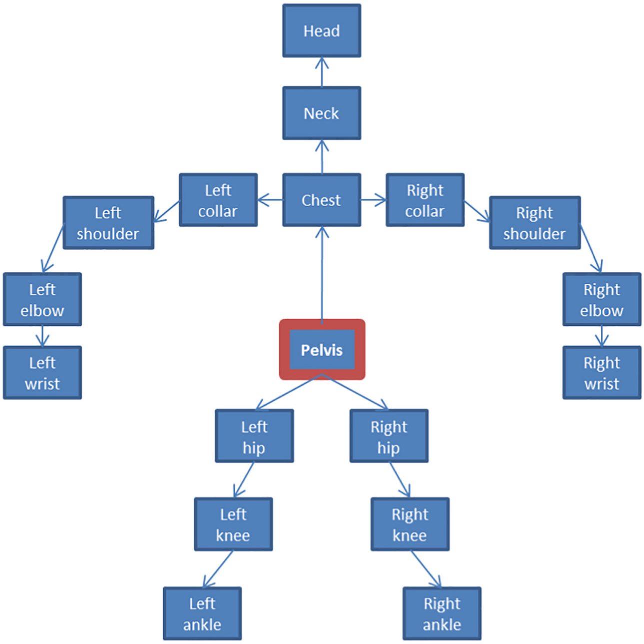

Fig. 1. Schematic visualization of the skeleton.

Forty-one landmarks available in the CAESAR database, such as olecranon, humeral epicondyle lateral, substernal are selected on the average body shape. Because of the correspondences, every vertex will remain at anatomically the same location, independent of shape.

A new skeleton of a Biovision Hierarchy (BVH) character animation file [6] was generated by calculating the optimal joint locations relative to these landmarks. Next, the skeleton is parented to the body shape by calculating skinning weights [7]. As a result, the pose of that body shape can be adapted. This means it can be adapted manually or a pre-defined movement can be executed.

2.3 Modification of Movement File

Motion is defined per frame, by a rotation offset per joint from the original skeleton. The body shapes available in the CAESAR database are standing in A-pose, as shown in Fig. 2. Therefore, the BVH files have to be adapted from T-pose to A-pose, as shown in Fig. 2. It is not sufficient to only convert the rest pose, as the motion is defined as rotation of the joints in rest pose. To solve this problem, we wrote Python code that can be run in Blender [8]. This code allows one to change the rest pose to the current adapted pose in Blender and to copy the original joint position to the new skeleton per frame.

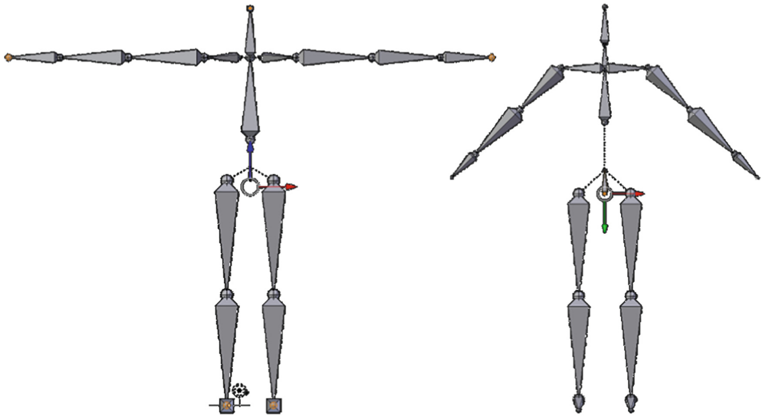

Fig. 2. The skeleton in rest pose. Left: T-pose, right: A-pose.

A skeleton $S \in \mathbb{R}^{3 \times j}$ is defined as a set of j joints $J \in \mathbb{R}^3$, whereas every joint per frame contains a rotation matrix $R \in \mathbb{R}^{3 \times 3}$ from the rest pose to the pose of the current frame.

$$S = \left[J_1\, J_2\, J_3 \ldots J_j\right] \tag{4}$$

$$R = \begin{bmatrix} m_{00} & m_{01} & m_{02} \\ m_{10} & m_{11} & m_{12} \\ m_{20} & m_{21} & m_{22} \end{bmatrix} \tag{5}$$

The workflow is as follows: first, the original skeleton $S_O \in \mathbb{R}^{3 \times j}$ is manually put in A-pose by rotating the joints, by a transformation T, resulting in a transformed skeleton $S_T \in \mathbb{R}^{3 \times j}$. The new pose is applied as rest pose of the skeleton:

$$S_T = T \times S_o \tag{6}$$

The following step is to update the actions per frame, as the movement is defined by rotation of the joints in rest pose. As a first step, the skeleton S_T is translated in a way so the root joints, in this case the pelvis, are on the same location. The copied joints are rotated to match the orientation of the target joints. This is done by inverting the rest pose matrix and multiplying this with the rotation matrix of the current inverse of the rotation matrix of the parent joint and the rotation matrix of the parent joint in resting position. The resulting rotation matrix has to be applied to the specific frame of the skeleton in A-pose as resting pose:

$$R_T^{'} = R_T^{-1} \times \text{parent}\left(R_{T,rest}\right) \times \text{parent}(R_T)^{-1} \times R_O \tag{7}$$

3 Experiments and Results

3.1 Building a Statistical Shape Model

A statistical shape model was built from the CAESAR database [9]. We selected 57 soldier-like (male, height 1m52–2m10, age 18y–35y, BMI 18.5–25) body shapes to build our model. The shapes were registered using the same template surface mesh, a digitally modeled body consisting of 100k uniformly distributed vertices. The average soldier, shown in Fig. 3, has a height of $1.84 \pm 0.07\,m$, a BMI of 22.4 ± 1.7 and is 27.9 ± 4.5 years old. From these meshes, posture variances were removed and a statistical shape model was built. In Fig. 4, the first three modes of variance of the SBSM are shown.

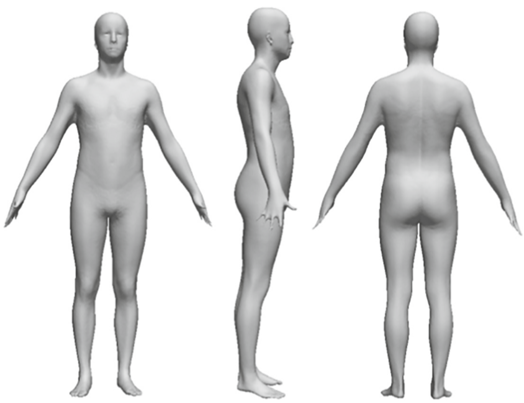

Fig. 3. Average soldier (male, height: 1.84 m, weight: 76.4 kg, age: 27.9 years, waist circumference: 846 mm, chest circumference: 951 mm, hip circumference: 990 mm, arm length: 654 mm, crotch height: 873 mm, knee height: 570 mm, shoulder breadth: 466 mm, sitting height: 953 mm, thigh circumference: 568 mm, BMI: 22.4).

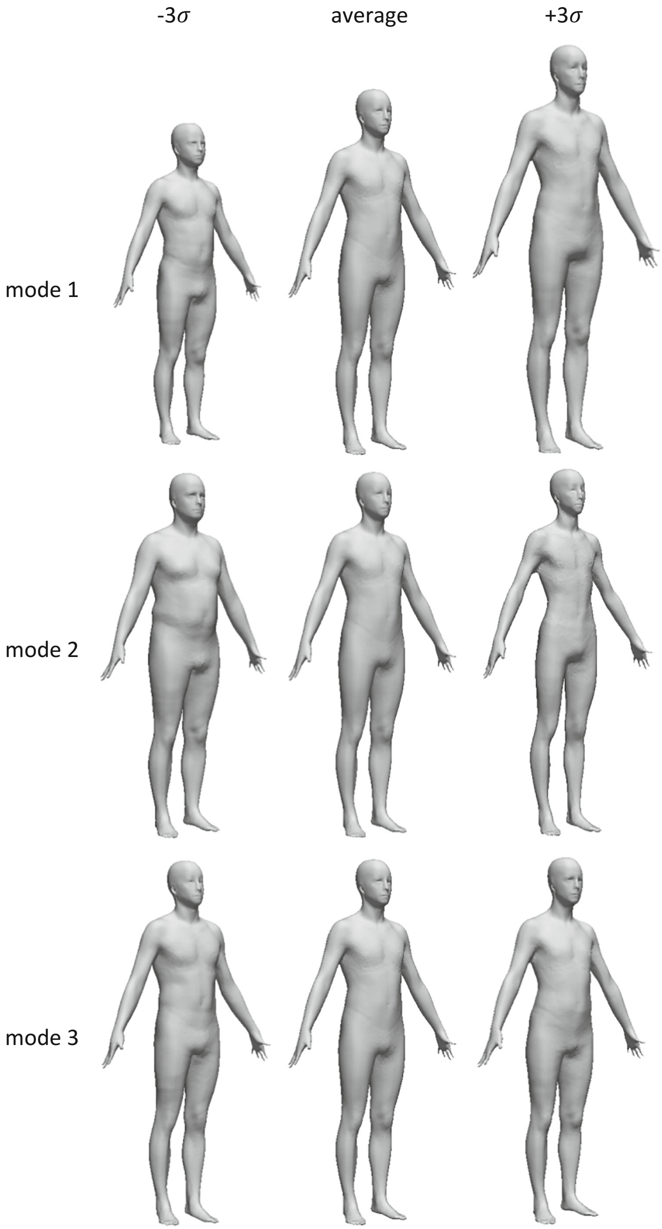

Fig. 4. The first three eigenmodes of the soldier SBSM plus and minus three standard deviations (σ) and the average body shape. The first mode mainly describes stature, the second mode mainly describes BMI, and the third mode mainly describes muscularity.

3.2 Shape Prediction and Skeleton Generation

A user interface was designed in which the following values can be specified: height, weight, age, waist circumference, chest circumference, hip circumference, arm length, crotch height, knee height, shoulder breadth, sitting height, and thigh circumference. We acquired the movement of a walking soldier using an inertial motion tracking system. After the shape had been generated, a new skeleton with associated movement was calculated. A screenshot of our implemented tool is shown in Fig. 5. This means that this feature will not be taken into account for shape prediction and the most plausible shape using the remaining values will be calculated.

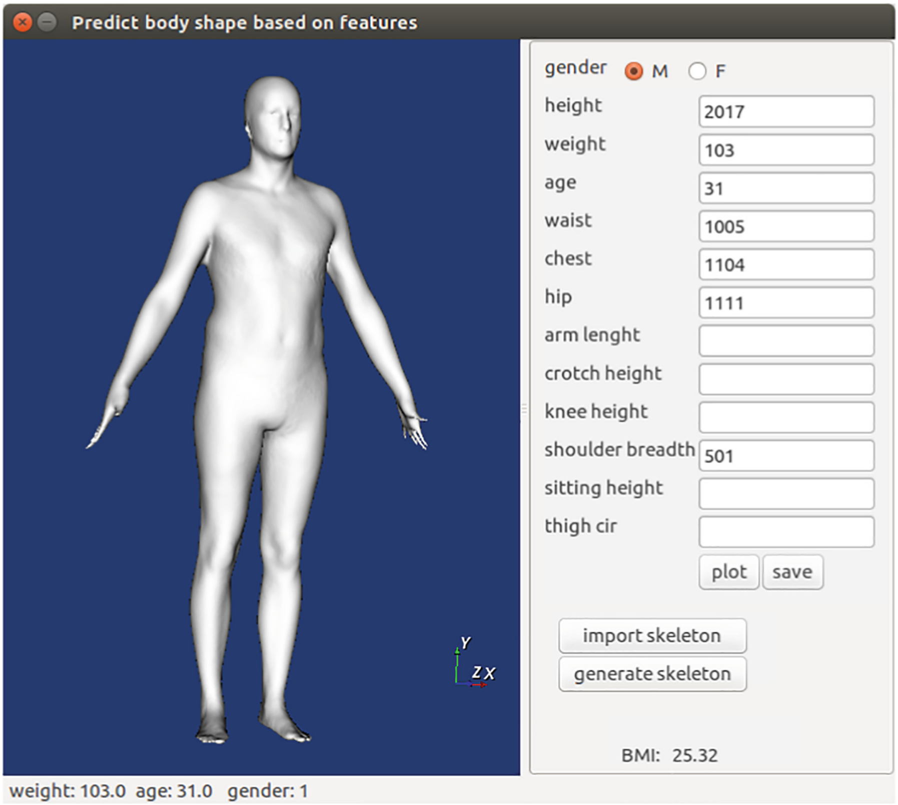

Fig. 5. Screenshot of body shape prediction and skeleton generation tool. The most plausible body shape of a male soldier with height 2.017 m, weight 103 kg, age 31, waist 100.5 cm, chest 110.4 cm, and shoulder breadth 50.1 cm is generated. The remaining values were unknown, so these values were not taken into account.

3.3 Adding Movement

The generated mesh and associated skeleton were imported in Blender, where the skeleton was parented to the mesh using automatic weights [7]. This approach resulted in a realistic body shape in motion, as can be seen in Fig. 6.

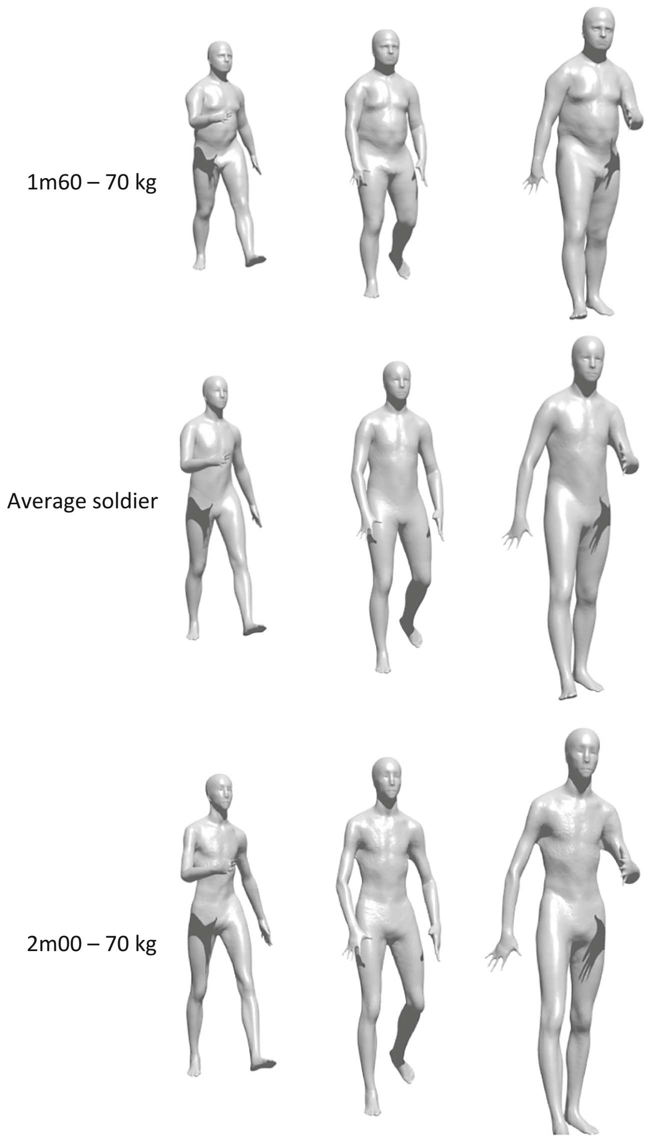

Fig. 6. Examples of walking soldiers with different body shapes.

4 Conclusion

We proposed an automatic technique to rig a statistical body shape model, allowing to simulate movement on a whole range of body shapes. Results show that our framework leads to detailed, realistic body shapes, moving in a natural way. This is especially useful for accessibility testing, e.g. when designing a vehicle, where the driver has to be able to perform specific movements to operate it in a correct way, while space is limited, or when optimizing comfort in wearing gear. Furthermore, static pose is adaptable by manipulating the armature, which is useful for designing near body products that require the body to be in a pose that is difficult to scan.

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