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Synthesizing Animatable Body Models with Parameterized Shape Modifications

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Abstract

Based on an existing modeller that can generate realistic and controllable whole-body models, we introduce our modifier synthesizer for obtaining higher level of manipulations of body models by using parameters such as fat percentage and hip-to-waist ratio. Users are assisted in automatically modifying an existing model by controlling the parameters provided. On any synthesized model, the underlying bone and skin structure is properly adjusted, so that the model remains completely animatable using the underlying skeleton. Based on statistical analysis of data models, we demonstrate the use of body attributes as parameters in controlling the shape modification of the body models while maintaining the distinctiveness of the individual as much as possible.

Keywords:

Human body modelling, regression, examples, 3D scanned data, somatotyping

1. Introduction

In Computer Graphics, it is essential to be able to generate and control realistic human models at an interactive time. Human modeling has thus attracted a good deal of attention in the past few decades. In particular, a variety of methodologies that have been specially developed for human body modeling are available nowadays, with which one can capture and digitize shapes and sizes of human bodies that exist in the real world. In addition, 3D range scanners are becoming increasingly available. Unfortunately, they are restricted to recoding shapes that can be observed - there is no simple means of automatically modifying the shapes once they have been created.

An automatic, example based modelling technique was recently introduced by Seo and Magnenat-Thalmann [10], for synthesizing body models from a number of anthropometric size parameters. Using dozens of 3D scanned data as examples, realistic, immediately controllable, whole body models were generated. One limitation of that modelling synthesizer is that a unique, identical model is produced given the same set of parameters. Often, we want to start with a particular individual to apply modifications according to certain attributes while keeping identifiable characteristics of the physique. A typical example could be: how a person looks like when someone loses his/her weight. This challenging problem has recently been addressed in computer graphics, specifically in the domain of facial modelling. Blanz and Vetter [2] use example database models from scanners and a linear function that maps facial attributes (gender, weight, and expression) onto the 3D model. Kähler et al [7] make use of anthropometric data to calculate the landmark-based facial deformation according to changes in growth and age. Our goal here is to introduce body shape control for obtaining variation of the body geometry according to certain body attributes, whilst keeping the distinctiveness of the individual as much as possible.

Our approach is to construct regression models, from captured body geometry data of real people that are in correspondence. After calibrating and annotating the data with corresponding shape measure, linear regression models are constructed for each component of the geometry. Then the shape modification on a given model is obtained by the deformation, guided by the regression model.

We begin by briefly describing our model representation and shape parameters. We then present our method for parameterized shape modifications. Finally, we discuss results of our approach.

2. Representation

The system maintains a template model, which is composed of skin and skeleton, without intermediate layers representing the fat tissue and/or muscles. The

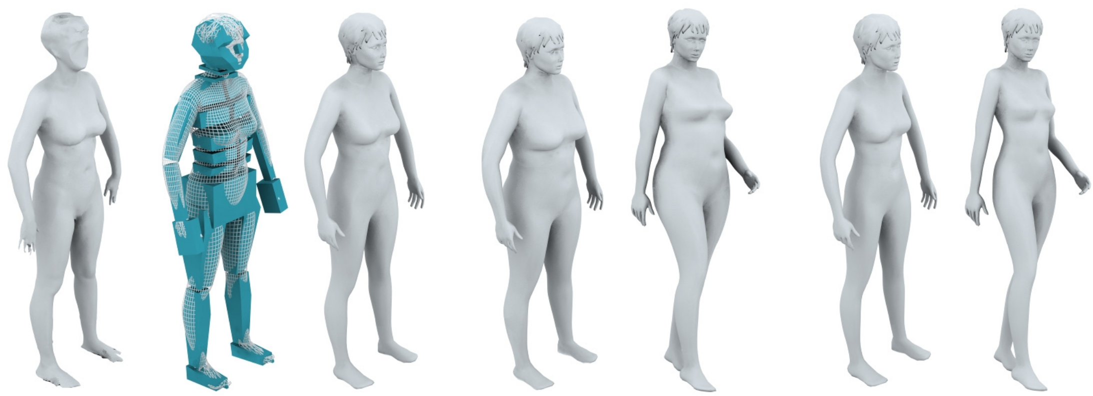

Figure 1: *Synthesis of human bodies by our synthesizer. (a) scan data; (b) template model with animation structure is fitted to the scan data; (c) the fitted template mesh (d) modification of the physique (fat percent 38%) and modified posture; (e) modification of the physique (fat percent 22%) and modified posture.*

skin is attached to the skeleton through *skinning* [8], in order to obtain smooth skin deformation whilst the joints are transformed. All our data models, which are acquired mostly from Tecmath 3D range scanner [11], are assumed to be in correspondence (i.e. they share the same topology), which we obtain by conforming the template model onto each scanned models. An assumption made here is that any body geometry can be obtained by deforming the template model. A number of existing methods such as [4] and [10] could be successfully used. In this work, we adopt a feature-based method presented by Seo and Magnenat-Thalmann [10]. In Figure 1(a)~(c), a scan data along with the conformed template model is illustrated.

The deformation of the template model to acquire a new one has two distinct entities, namely the *skeleton* and *displacement* components of the deformation. The skeleton component is the linear approximation of the physique, which is primarily determined by the joint transformations through the skinning. The displacement component is essentially vertex displacements, which, when added to the skin surface resulting from the skeletal deformation, depicts the detailed shape of the body. Thus, we denote the skeleton component as

$$J = (t_x^1, t_y^1, t_z^1, s_x^1, s_y^1, s_z^1, t_x^2, ..., t_y^m, t_z^m, s_x^m, s_y^m, s_z^m)^T \in R^{6m},$$

where t_x^j and s_x^j are the translation and scale of joint *j* (*j* =1,…,*m*) along the *x*-axis, with the rotation excluded. Similarly, the displacement component is represented by

$$D = (d_x^1, d_y^1, d_z^1, d_x^2, ..., d_y^n, d_z^n)^T \in R^{3n},$$

where d_x^v is the displacement of vertex *v* (*v* =1,…,*n*) along *x*-axis on the skin mesh. We therefore represent the geometry by a body vector *B* = (*J, D*).

Although the transformations computed independently for each bone may be used as above, significant redundancy exists in the bone transformations, exhibiting similar transformations among neighboring bones. A similar redundancy exists as regards the skin displacement. Thus we seek simplifications that allow the synthesizer to operate on compact vector space. In both cases, we adopt PCA [9], one of the common techniques to reduce data dimensionality. Upon finding the orthogonal basis called eigen vectors, the original data vector ***x*** of dimension *n* can be represented by the projection of itself onto the first *M* (<< *n*) eigen vectors that corresponds to the *M* largest eigen values. In our case, the first 25 bases were enough to describe 99% of variations among the data so a 25-dimensional space was formed. Thus, the final representation of the body vector is composed of six sets of 25 coefficients that are obtained by projecting the initial body vector onto each set of eigenvectors. In this work, we use t_{tx}^i, t_{sx}^i and δ_x^i to denote the *i*-th (*i*=1,…,25) coefficient of joint translation, scale, and vertex displacement, along the *x*-axis.

3. Shape control parameters

A prerequisite of parameterized modeling is a choice of control parameters. Body attributes such as hourglass, pear/apple shape are typically those that provide a global description and dramatically reduce the number of parameters. The closest metric that maps these attributes to numerals is hip-to-waist ratio (HWR; hip girth divided by the waist girth). Another metric that describes the global change of the physique is fat percentage. It however requires information that is not typically available from the scanned data. For example, in the 'anthropometric somatotyping' [3], skinfolds of four selected parts of the body are required to give a rating of approximate fat percentage. Fortunately, there are a number of empirical results that allow us to estimate the fat percentage from several anthropometric measurements [6]*. Here, we adopt HWR and fat percentage, and height as shape control parameters of the modifier synthesizer.

4. Modifier synthesizer

Our modifier synthesizer is built upon regression models, using shape parameters as estimators and each component of the body vector as response variables. Our example models are however, relatively small (n=60) and skewed. We therefore perform the sample calibration, as described in Section 3.2, prior to the regression modeling.

Sample calibration

We observed that tall-slim and short-overweight bodies are overrepresented in our database, exhibiting a high correlation between the height and the fat percentage (r=-2.6155, p<0.0001). Directly using such data that contains unequal distribution may result in false estimation by the modifier synthesizer. We use sample calibration [5] to avoid such erroneous estimation. It improves the representativeness of the sample in terms of the size, distribution and characteristics of the population by assigning a weight to each element of the sample. Here, we wish to determine the weights for each sample so that the linear function that maps the height to the fat percentage has the slope 0.

Consider the sample consisting of n elements. Associated with each element k are a target variable y_k and a vector $\mathbf{x}_k$ of p auxiliary variables. Consider also that $\mathbf{x}_k$'s are correlated with y_k by the regression $Y = XB$, where $(X)_{kj}=x_k^j$ denotes the jth variable of element k, Y denotes the vector of n target variables, and the correlation vector $B=[b_1,..\ b_n]^T$ is known for the population.

The calibration method aims to compute a weight w_k for each element so that the sample distribution of the variables X agrees with the population distribution. The calibration problem can be formulated as follows:

Problem 1: Minimize the distance

$$\sum_{k=1}^{n} G(w_k) \quad (1)$$

subject to a calibration constraint defined by the weighted least square equation:

$$X^T W_m XB = X^T W_m Y \quad (2)$$

where $W_m = \text{diag}(w_1, \ldots, w_n)$.

The so-called distance function G measures the difference between the original weight values (uniform weighting of 1.0 in our case) and the values w_k. The objective is to derive new weights that are as close as possible to the original weights. In our case, the regression model is linear (p =1), x_i^j and y_i are the fat percentages raised to the power of j-1 and the height of element i, respectively. The coefficient vector B is $[b_1,0]^T$. Taking this value, the development of the Equation (2) yields:

$$L \cdot W_v = \begin{bmatrix} x_1^1(b_1 - y_1) & \cdots & x_n^1(b_1 - y_n) \\ \vdots & \ddots & \vdots \\ x_1^p(b_1 - y_1) & \cdots & x_n^p(b_1 - y_n) \end{bmatrix} \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} = 0 \quad (3)$$

The linear system in (3) is an underdetermined, with $n > p$. These weights have to be computed in a way that the equation (1) is minimized. To find a solution to (3) with (1) minimized, we replace w_k with $w_k' + 1$ and rewrite (3) as:

$$L \cdot W_v' = -L, \quad (4)$$

where $W_v' = [w_1', \ldots w_n']^T$. In addition, we add one more equation

$$\sum_{k=1}^{n} w_k' = 0$$

to (4), since we want the mean of the weights w_k to be equal to 1. The distance function G used in our approach is the quadratic function $G(w_k) = 1/2(w_k - 1)^2$ [5]. The underdetermined linear system is solved using Cholesky decomposition [9] that finds the least norm solution.

Parameterized shape modification of individual models

Similarly with the problem of the parameter-driven individual modeling synthesizer, we wish to obtain the modification of the body geometry as a function evaluation of the chosen parameter, in our case fat percentage. Clearly, we can make use of the examples to derive such function. Unlike the modeling synthesizer, however, we would like some of the attributes, i.e. those which characterize a particular individual model to remain unchanged as much as possible during the modification, whilst other attributes are expected to be changed according to the control parameter. In general, it is difficult to identify what is invariant in an individual through changes from various factors (sport, diet, aging,

* The regression equation used to estimate the fat percentage of a Caucasian woman's body is: $163.205 \times \log_{10}(abdomen + hip - neck) - 97.684 \times \log_{10}(height) - 78.387$.

etc.). In addition, 3D body examples of an individual under various changes in his/her appearance are rare. (Although one can relatively easily obtain such examples when the aim is to build pose parameter space, as used in Allen et al [1].) Therefore, the problem of identifying (i) characterizing geometric elements of an individual and (ii) controllable elements from the given examples needs to be solved.

We approach the problem by first computing the linear regression model between a shape parameter and each element of the body vector, as partly shown in Figure 2. The formulation of the regression model based on the weighted least square method is:

$$\alpha = (X^T W_m X)^{-1} (X^T W_m Y),$$

where

W_m: the sampling weight matrix defined in Section 6.1,

X: the shape parameter values of every element in the sample,

Y: the ith element of the body vector, b_i of every element in the sample,

α: the coefficients of the regression function $E_i(x)$.

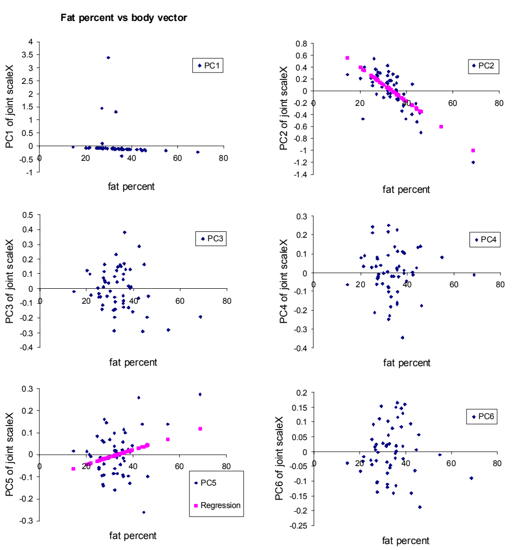

Figure 2: *Fat percentage and 6 principal components of joints 'scaleX' body vector.*

For a given shape parameter x, the regression function $E_i(x)$ gives the average value $\hat{b}_i$ of b_i's (see Figure 3). The difference $e_i = b_i - \hat{b}_i$ is called the residual of the regression. we consider this residual value as the distinctiveness of the body, i.e. the deviation of the body vector component from its average value. Similarly to Kähler et al [7], we assume that the body component keeps its variance from the statistical mean over the changes: a shoulder that is relatively large will remain large. By computing the regression functions $E_i(x)$ for every b_i, it is possible to compute the average body for a given a shape parameter. Therefore, for a given body vector for which we know the shape parameter, we can compute the residual value of all the components of the body vector. Given x_{src} the shape parameter of the input body and x_{trg} the shape parameter for which we want to generate the body, the new value of b_i' is given by:

$$b_i' = E_i(x_{trg}) + (b_i - E_i(x_{src})).$$

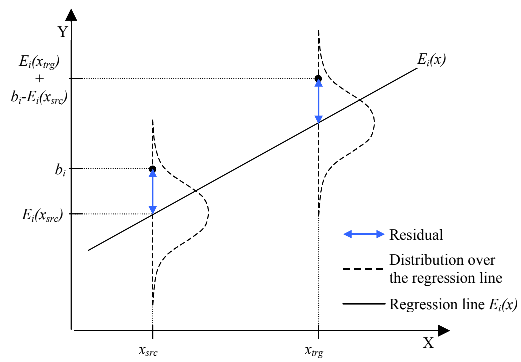

Figure 3. *Shape variation with the regression line and the residual.*

5. Results and discussion

Figure 4 shows some of results obtained by shape modification. It is clear that the bodies remain identifiable during the modification. All our models are animatable using motion sequence, through the update of the vertex-to-bone weight that is initially assigned to the template model. (See Appendix A for the skin attachment recalculation). In Figure 5, a captured, key frame based motion data sequence is used for the animation of our models.

While there exists a good deal of consistency between our model and real bodies, our regression models on the body vector should be differentiated from those on anthropometric body measurements. The regression model of 'scale_x' of the bone, for instance, shows that the physical fat of subjects is partly captured by, and interpreted as, the linearity in the model. The regression models for the skeleton components and displacements are shown in Table 1 and Table 2, respectively.

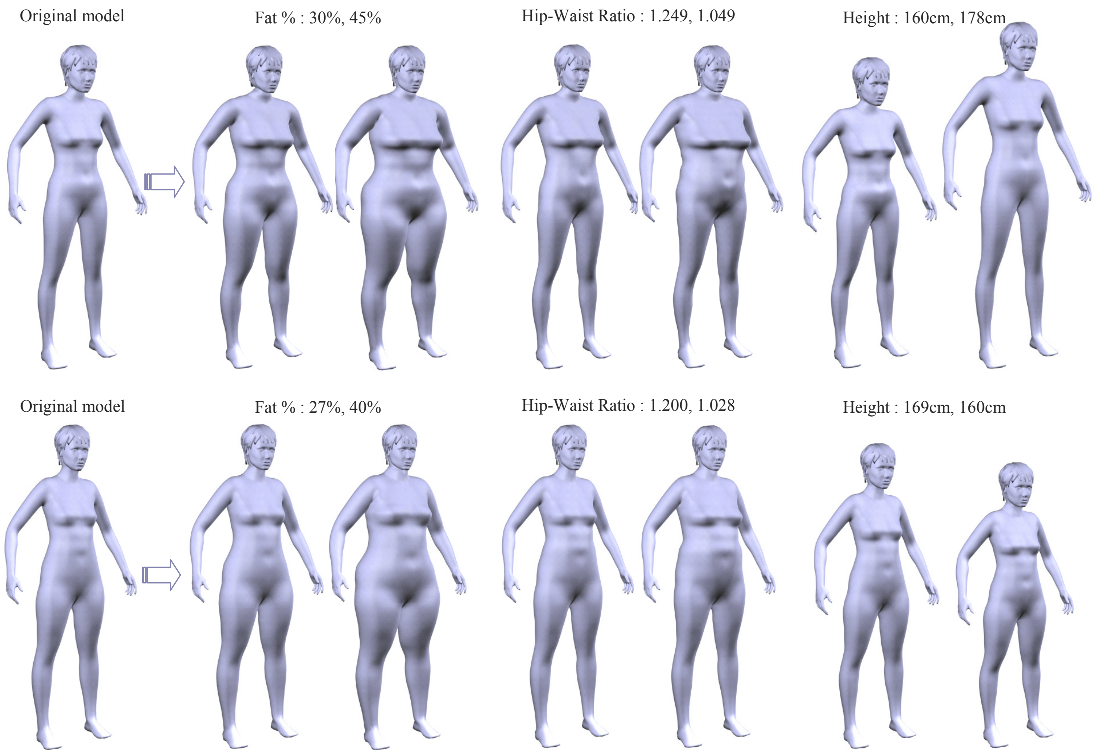

Figure 4: *Modification of two individuals controlled by fat percent,hip-waist ratio and height.*

Table 1. Linear regression model on the skeleton component.

Explanary variable	regression coefficient	standard error	*F*-ratio	*p*-value
δ_x^1	-2.9363	0.039295	8.621829	0.004872
δ_x^5	-0.06207	0.029464	4.438548	0.039797
δ_x^6	0.121447	0.024977	23.64189	1.04e-05
δ_y^1	0.214258	0.04131	26.90133	3.3e-06
δ_y^4	-0.07232	0.03268	4.897688	0.031139
δ_y^5	0.107049	0.033195	10.39955	0.002141
δ_z^2	-0.08119	0.028622	8.046944	0.006405
δ_z^3	-0.06428	0.025047	6.58599	0.013085
δ_z^{10}	-0.064	0.012807	24.97014	6.48e-06

Table 2. Linear regression model on the displacement component.

Explanary variable	regression coefficient	standard error	*F*-ratio	*p*-value
t_{sx}^2	-0.02849	0.003272	75.82538	7.23e-12
t_{sx}^5	0.003328	0.001485	5.024998	0.029115
t_{sx}^7	-0.00261	0.001122	5.420798	0.023673
t_{sx}^9	-0.00184	0.000738	6.186507	0.015994
t_{sy}^1	0.043125	0.004694	84.39235	1.26e-12
t_{sz}^1	-0.00975	0.003704	6.926509	0.011048
t_{tx}^2	0.025454	0.012929	3.876025	0.054122
t_{tx}^3	0.02357	0.01203	3.838827	0.05525
t_{tx}^6	0.022441	0.007838	8.196972	0.005961
t_{ty}^3	-0.06049	0.018584	10.59697	0.001958
t_{tz}^5	0.07172	0.025202	8.098249	0.00625
t_{tz}^8	0.03009	0.014531	4.287934	0.043178

Body vectors and their distribution also depend on the initial skinning. When there is a strong weight on the upper arm, a small-scale value will be sufficient to result in a large arm while a large scale is required to have the same effect when the attachment is loose. An automatic refinement of the skin attachment to obtain an optimal skinning could be found, so that the variation of body vectors for all examples is minimized, for instance.

Although in this work we have experimented mainly with size and shape parameters, there are other types of criteria that we believe are worth exploring. Some examples are sports, aging, and ethnicity. Combining these parameters with the sizing parameters is certainly one possibility to extend our system.

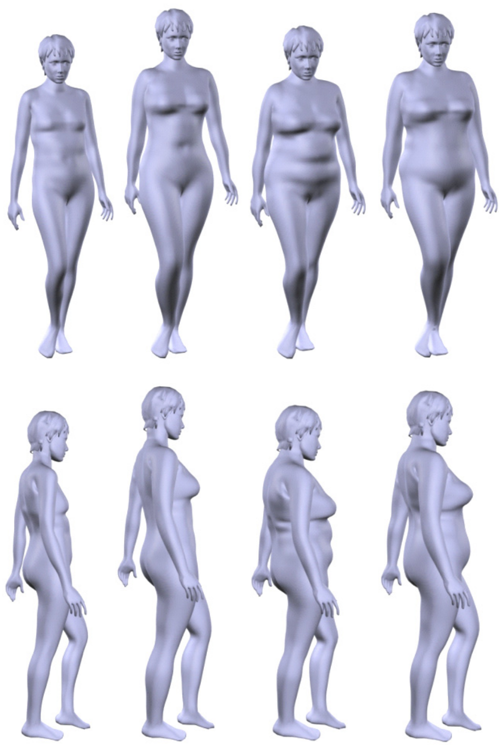

Figure 5. *Motion captured animation applied to four of our models.*

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Appendix A: Skin attachment recalculation

Once the body shape has been modified through the displacement, the skin attachment data needs to be adapted accordingly so that the model retains smooth skin deformation capability. Generally, the deformed vertex location p is computed as

$$p = \sum_{i=1}^{n} w_i M_i D_i^{-1} p_d$$

where M_i and w_i are the transformation matrix and influence weight of the i-th influencing bone, D_i is the transformation matrix of i-th influencing bone at the time of skin attachment (in most cases D_i's are chosen to be so called dress-pose, with open arms and moderately open legs) and p_d is the location of p at the dress-pose, described in global coordinate system.

Recomputing the skin attachment data involves updating the location p_d for each of its influencing bone. Note that the model has to be back into the dress-pose when the recalculation takes place.