

Semantic Parametric Reshaping of Human Body Models

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Abstract—We develop a novel approach to generate human body models in a variety of shapes and poses via tuning semantic parameters. Our approach is investigated with datasets of up to 3000 scanned body models which have been placed in point to point correspondence. Correspondence is established by non-rigid deformation of a template mesh. The large dataset allows a local model to be learned robustly, in which individual parts of the human body can be accurately reshaped according to semantic parameters. We evaluate performance on two datasets and find that our model outperforms existing methods.

Keywords—semantic parameters; local mapping; reshaping; deformation;

I. INTRODUCTION

Human shape modeling plays an important role in many applications ranging from digital entertainment and garment manufacturing, to simulation and training. However, creating human shape models remains a tedious and labor intensive task. There are difficulties in acquisition, merging, and editing of human shapes.

One approach to editing body meshes is to learn a model of how the mesh deforms with respect to shape and pose. With this model, new body shapes can be generated. However, previous reshaping methods either lack semantically meaningful parameters, or lead to unexpected results from over-fitting. For example, when we adjust the chest circumference, the waist circumference may have undesirable change. To address this problem, in this paper we present SPRING, a novel Semantic Parametric ReshapING method.

More specifically, we start by bringing a large data set of body scans into correspondence. We develop a non-rigid registration algorithm with regularization, to register the raw range scans in the dataset with a template mesh. As a result, our database consists of the the warped templates corresponding to the raw scans, and has the critical point-to-point correspondences that are required to learn the body shape constraints and variations.

Several mathematical models [2], [8], [12], [14], [16] have been proposed to model human pose and shape variation. We use a model in which pose and shape variations are learned as separate terms of a unified model. After the transformations of shape variation across different individuals are obtained, Principal Component Analysis (PCA) is used to

generate a subspace of body shape deformations [20] and [9]. This portion of our analysis is similar to prior work and we refer to these methods as *Global Mapping*.

We extend the method with a novel regression model, which we refer to as *Local Mapping*, to explore the space of detailed semantic attributes. For each triangular face, a linear mapping between semantic attribute parameters and the corresponding shape variations is learned, and a mapping constraint is introduced to avoid the over-fitting problem.

The primary contribution of this paper is a novel method to reshape models of the human body using semantic parameters. We support this contribution with experiments to verify the validity of our model and to compare the results of our reshaping method with the state-of-art reshaping method. Results show that our reshaping method compares well in terms of accuracy and robustness.

II. RELATED WORK

Correspondences: To obtain a dataset of human bodies, laser range scans of different individuals need to be collected. After that, a method to establish point-to-point correspondences between them is needed. A common method is to use a template mesh to fit all the target shapes. It was first applied to heads and faces. For example in the work of Marschner *et al.* [10], an energy-minimization framework is introduced to guide the fitting process by using a surface smoothness term. Allen *et al.* [1] introduced this framework into the domain of whole body models and made improvements to address hole-filling and detail from the template surface. Sumner and Popović [17] used a similar method in their work of deformation transfer. A deformation identity term is added into the energy function to prevent drastic change caused by the smoothness term. All of these methods minimize this function in two stages and the process is can be thought of as a non-rigid deformation of the template mesh onto each target model. We follow a similar strategy.

Morphable Model: Several mathematical models [2], [8], [12], [14], [16] have been proposed to model human pose and shape variation. SCAPE [3] learns separate models of body deformation across poses and individuals. One model is accounting for changes in pose and another is accounting

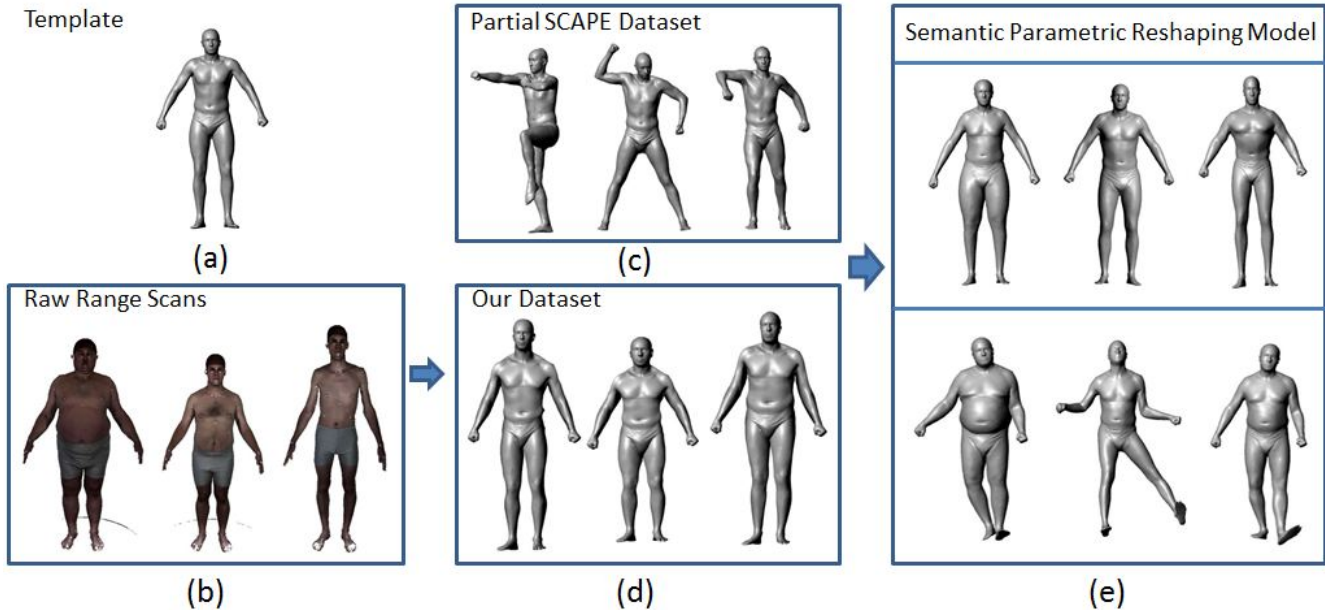


Figure 1. An overview of our pipeline to build a large scale dataset and reshape models of the human body. First, we fit a template mesh (a), to each raw range scan (b) using a non-rigid registration method. After this, our body shape dataset (d) has point-to-point correspondences with our separately obtained pose dataset (c). Finally, we propose a novel reshaping method to generate new models of human body according to semantic parameters of human body shape and pose (e).

for differences in body shape. However this method has an inherent problem that pose and shape are treated independently. Allen [2] uses maximum posteriori estimation of identity and pose-dependent body shape variation. However since dimensionality of the nonlinear function is so high, the optimization procedure is expensive. Hasler *et al.* [8] propose a statistical model which jointly encodes pose and body shape. The primary advantage of this approach is correlations between body and shape are encoded. Chen *et al.* [5] present another approach which explores a tensor decomposition technique. To preserve the dependency between pose and shape parameters, a joint function is used to model the deformation, and then a tensor-based method is introduced which has two parts—one is for individual body segment and the other is for the whole body. Unlike these work, Neumann *et al.* [12] propose a semi-parametric learning approach to build a data-driven model which can produce non-linear muscle deformation effects. Based on their work, many applications have been developed, such as shape and pose estimation [7] [4] [19] and deformable cloth models [6].

Semantic Modeling: To explore body shape variation across different individuals, Allen *et al.* [1] perform PCA over the displacements of the template points. Seo and Thalmann [15] also use PCA over point displacements to represent the non-rigid component of body deformation. However point displacement is not robust when two individuals vary greatly in scale. To address this problem, following the work

by Sumner and Popović [17], Angelov [3] performed PCA over the transformation matrices between the template shape and the other models. By representing the deformation of each triangle using a 3×3 matrix, scaling of the deformation can be maintained.

Although PCA can be utilized to characterize the space of human shape variation, it does not provide a direct and intuitive way to explore the space of the semantic parameters, such as height and weight. Allen [1] introduces a linear regression method to learn a linear mapping between 7 semantic parameters and the PCA coefficients. Zhou [20] and Jain [9] follow a similar method. But 7 semantic parameters are not adequate to reconstruct a human model in most cases. So we define a new set of semantic parameters, which can be used to reshape human body models in detail. Unfortunately, when the methods proposed in these papers are used on our detailed semantic parameters, overfitting occurs and correct independent variation of parameters is not possible. To avoid this problem, we propose a novel method to explore the space of detailed semantic parameters.

Localized Deformation: Localized deformation is a popular research topic in recent years. Meyer *et al.* [11] apply the Key Point Subspace Acceleration (KPSA) technique to character animation. With a few of the basis vectors after the Varimax rotation, the motions are much more localized. Neumann *et al.* [13] propose another method by extending the theory of sparse matrix decompositions to extract sparse and spatially localized deformation modes from an animated

mesh sequence. Though this model can produce spatially localized and semantically meaningful effects by exaggerating certain components, it is not suitable for our work that the reconstructed human model should confirm to the precise semantic parameters, not just a trend.

III. BUILDING A LARGE SCALE DATASET OF HUMAN BODY

Before a model of human shape and pose can be learned, a training dataset needs to be produced. We obtain body meshes from existing datasets, establish correspondence, and fill holes.

A. Source datasets

We make use of several existing datasets. MPI distributes body data which includes both variations in shape and pose [8]. This data is already in correspondence, however the dataset is neither large nor high resolution. We use this as our small dataset.

In order to build a large dataset we combine two existing sources. Our source meshes for body shape are laser range scans from the CAESAR dataset, which includes thousands of models. Each range scan in the CAESAR dataset has about 150,000 – 200,000 vertices and 73 markers. Unfortunately this data is not in correspondence and contains many holes.

Our source for body pose data is the SCAPE method by Anguelov [3]. Although the original work made use of both shape and pose data, only the pose data is distributed, together with a template model and correspondences. We use this data which consists of 70 poses, each with 12,500 vertices and 25,000 facets.

We assemble our large dataset by bringing the template provided with SCAPE into correspondence with the body shape data provided by CAESAR.

A range scan from the CAESAR dataset is shown in Figure 2(a). The template provided by SCAPE is shown in Figure 2(b), with colors showing segmentation into 16 rigid parts.

B. Establishing Point-to-point Correspondences

To obtain meshes with point-to-point correspondences, a method inspired by Allen *et al.* [1] and Sumner *et al.* [17] has been taken. A template mesh is used to fit to each raw scan. To compute the deformed vertices, a set of affine transformations are defined to minimize a energy function which consists of four parts: E_S , E_I , E_C and E_M . The first two terms regularize, and the second two terms enforce a proper fitting to the target scan. For details, please refer to [1] [17]. An iterative approach [1] similar to ICP is used to minimize this energy function. Since this method warps the template onto each raw scan, meshes in our dataset have point-to-point correspondences with the template and each other, while their shapes are very close to the corresponding

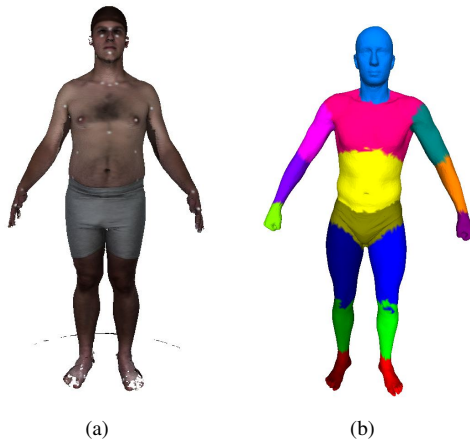


Figure 2. A raw range scan from the CAESAR dataset (a), and our template obtained from SCAPE (b).

raw scans. Figure 3 shows examples of some meshes in our dataset.

C. Hole Filling and Hand Replacement

Since the range scans, D , from our dataset have holes in some parts, such as under the arms and on top of the head, the method above needs to be modified. If the closet point on D to a deformed template point is located on the boundary of the holes, we set the weight corresponding to E_C to 0. The deformation of these points are affected mainly by the smoothness term. As is shown in Figure 4, the holes are filled smoothly.

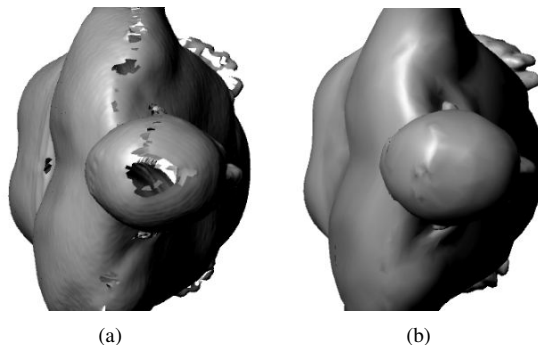


Figure 4. Raw scanned meshes contain many holes as shown in (a). Using our template, these holes can be filled as shown in (b).

Our template is different from the raw scans in hand pose, one is fist and the other is stretched. Thus fitting in this region of D would be impossible. To address this problem, we identify the points belonging to the hand by labeling them on the template mesh and ignore the closet points on D in this region. That is to say, we favor the template surface over the scanned surface when fitting this part and these points are also affected mainly by the smoothness term. Figure 5 shows the result that the junction looks quite good without any distortion.

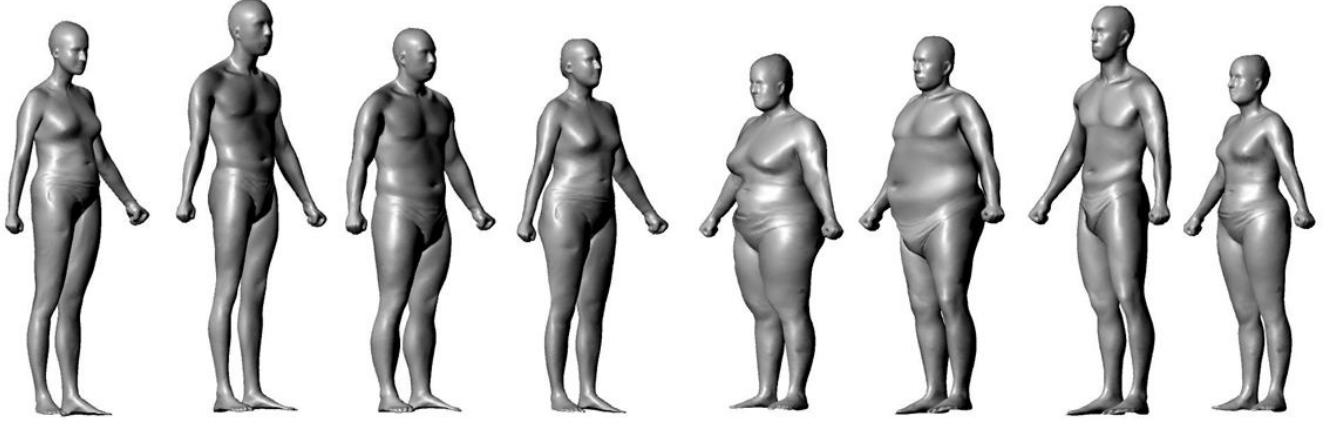


Figure 3. By fitting a template to many raw range scans, meshes with a wide variety of body shapes having point-to-point correspondences can be obtained.

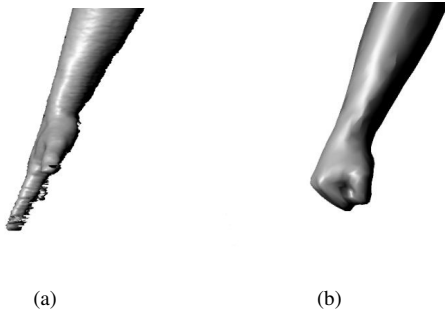


Figure 5. The template hand is used to replace the scanned hand. The raw scanned hand is in an extended pose as shown in (a). The template hand can be fit to M without any distortion, as shown in (b).

IV. SEMANTIC PARAMETRIC RESHAPING

Since point-to-point correspondences between all body shapes has been established, we can learn a human shape model incorporating all scans. We begin with the SCAPE model to learn the pose and shape deformation. After the transformation matrices of shape variation across different individuals are obtained, we introduce a regression model to explore the space of detailed semantic parameters.

A. Transformation Matrices of Shape Variation

To model the shape variation, we firstly separate the pose deformation by solving for a 3×3 transformation matrix Q_k for each triangle k in each mesh. After this, shape deformation matrix S_k can be obtained. For each mesh i , a $9 \times N$ (N is the number of triangles) vector \tilde{S}_i is regrouped from the shape deformation S^i . And then a linear subspace which generates the vector can be estimated by PCA.

$$\tilde{S}^i = \varphi_{U,\mu}(\beta^i) = \overline{U\beta^i + \mu} \quad (1)$$

where $U\beta^i + \mu$ is a reconstruction of the matrix coefficients from the PCA. For more details, please refer to [3].

B. Detailed Semantic Parametric Modeling

PCA coefficients can be used to characterize the space of human shape variation, but they do not have actual meaning as to anthropometry. To address this problem, we use a linear regression method to learn a linear mapping between semantic parameters and the model parameters.

1	forearm length	11 12	chest circumference
2	upper arm length	13 14	waist circumference
3	head height	15 16	hip circumference
4	neck height	17	thigh circumference
5	thigh length	18	knee circumference
6	calf length	19	calf circumference
7	foot length	20	ankle circumference
8	head circumference	21	check circumference
9	upper arm circumference	22	shoulder breadth
10	forearm circumference	23	upper body height

Table I
SEMANTIC PARAMETERS

In our experiments, we use 23 semantic parameters as enumerated in Table I, e.g., forearm length, neck height, head circumference and shoulder breadth. For chest, waist and hip circumference, two parameters are defined respectively: one is for breadth and the other for thickness, as shown in Figure 6.

One option is to learn the mapping between semantic parameters and PCA coefficients, a method we refer to as **Global Mapping**. This is similar to the method introduced by Allen [1]. Assuming we have L semantic parameters and the dimension of PCA space is k , the mapping can be represented as:

$$M [f_1 \dots f_L 1]^T = p \quad (2)$$

where M is a $k \times (L + 1)$ matrix, f_l (l is the index of semantic parameter) are the semantic parameter values

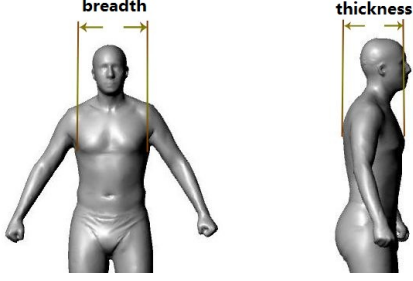


Figure 6. Two examples of semantic parameters, breadth and thickness of chest circumference.

of an individual, and p are the corresponding PCA coefficients. This mapping enables us to specify every semantic parameter offset. Let $\Delta f = [\Delta f_1 \dots \Delta f_L 0]^T$ denotes an parameter offset vector, PCA parameters offset can be represented as $\Delta p = M\Delta f$.

We found that the above model has difficulty with over-fitting especially when a smaller dataset is used. Since PCA coefficients do not have actual meaning as to anthropometry, we must treat all semantic parameters equally for each PCA coefficient. Consequently, the topology of human body is ignored. To address this problem we introduce **Local Mapping**, a method taking advantage of the constraints of topology of human body.

Local Mapping is a linear regression model which directly learns a mapping between semantic parameters and shape deformation matrices. Each shape deformation matrix S corresponds to a triangular face belonging to a certain rigid part. The template model has been segmented into 16 rigid parts beforehand and we just need to bind the semantic parameters to each parts. For example, forearm length and circumference belong to the forearm part.

For each triangular face, a $9 \times (L + 1)$ matrix N can be computed based on the following equation:

$$N \Phi([f_1 \dots f_L 1]^T, i) = s_i \quad (3)$$

where Φ is a function defining which parameters influence this face, i is the index of the face and s_i is a 9×1 vector regrouped from the 3×3 shape deformation matrix S_i .

The function of Φ is to decide which semantic parameters influence the triangular face. So we refine it as a vector dot producting the semantic parameters. And equation 3 can be rewritten as:

$$N([\phi_{i,1} \dots \phi_{i,L} 1]^T \times [f_1 \dots f_L 1]^T) = s_i \quad (4)$$

To compute $\phi_{i,l}$, we found that the following criteria which uses geodesic distance performed well. The nearest vertex C_j (j is the index of rigid part) to the mass of each rigid part P_j need to be found firstly. For each triangular face, we choose the nearest vertex to the mass of the face as starting point V_i . And then geodesic distance $D_{i,j}$ from

V_i to C_j is computed, just as shown in Figure 7. We use the distance $D_{i,j}$ to decide if rigid part P_j influence this face. If the distance is below a threshold ε , the semantic parameters belonging to this part are considered important by setting corresponding $\phi_{i,l}$ to 1 and otherwise to 0. The criteria intuitively conform to physiology that the adjacent parts of a human body have a certain relationship. These $\phi_{i,l}$ are only evaluated once on the template mesh.

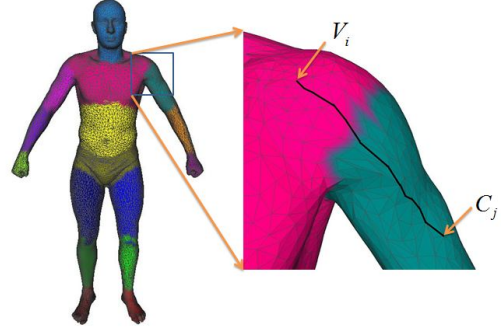


Figure 7. Geodesic distance. Taking a triangular face at shoulder as an example: V_i is the nearest vertex to the mass of the face and C_j is the nearest vertex to the mass of the forearm part P_j . The black line is the geodesic from V_i to C_j .

In this case, results are improved considerably but some problems still exist when the model is learned from the small dataset (e.g., when we modify the value of head height, the head circumference of the generated mesh is also changed). When the mapping is learned on the large dataset, results are quite satisfactory, as shown in Figure 8 and Figure 9.

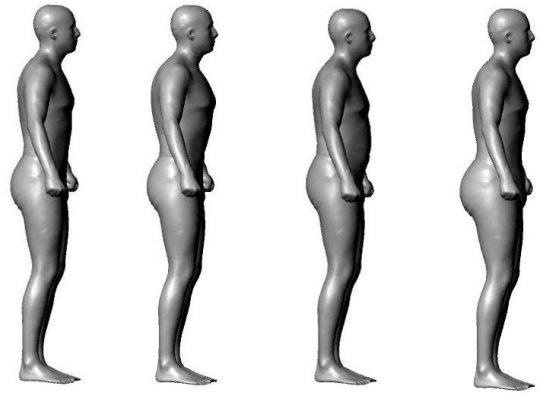


Figure 8. The first one is our template while the others are results generated by increasing the thickness of chest circumference, waist circumference and hip circumference in turn.

V. EXPERIMENTS

In order to evaluate our semantic model, we learned a linear mapping between semantic parameters and body shape deformation S based on both previous and our large datasets.

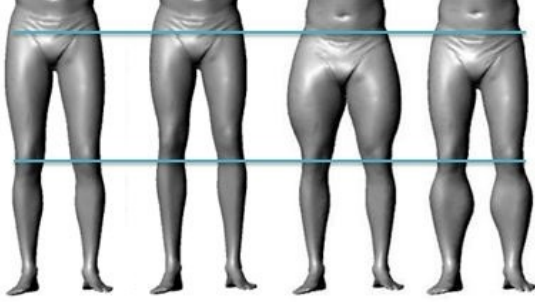


Figure 9. Results generated by increasing thigh length, calf length, thigh circumference and calf circumference in turn.

The previous dataset has 114 meshes, while our large dataset has more than 3000. Three sets of comparison are made between existing **Global Mapping** methods [1], and **Local Mapping** introduced in this paper.

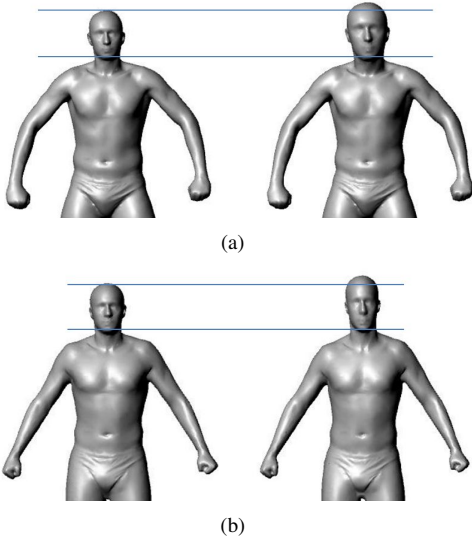


Figure 10. Results comparison: head height is increased. (a) result of global mapping using previous dataset; (b) result of local mapping based on our large dataset.

1) When head height is increased, results generated by different methods on different datasets are compared. As shown in Figure 10, the left one is template and the right is the generated result in each subimage. We observe that

- i. Not only the head height, head circumference is increased when using Global Mapping with the previous dataset.
- ii. Result is great that only the head height is increased when using Local Mapping based on our large dataset.

2) We increase thigh and calf circumference and results generated by different methods on different datasets are compared. As is shown in Figure 11, the left column

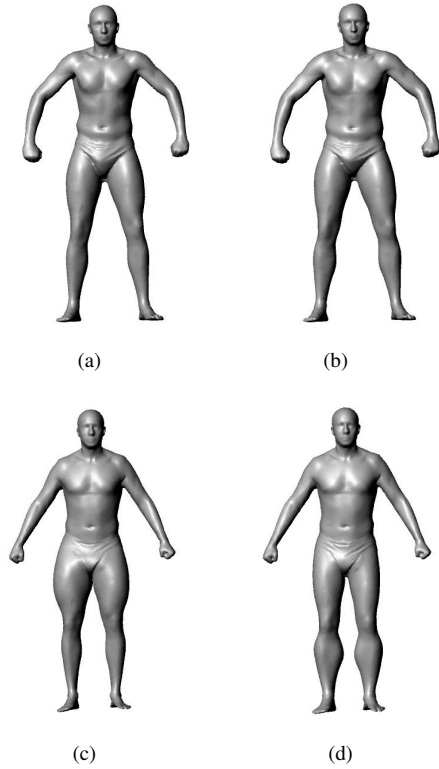


Figure 11. Results comparison: thigh and calf circumference are increased. (a) (b) results of global mapping based on previous dataset; (c) (d) results of local mapping based on the large dataset.

corresponds to increase of thigh circumference and the right to increase of calf circumference. We conclude that

- i. Thigh and calf have very little change when using Global Mapping based on the previous dataset. The global model is not sufficient to allow these changes.
- ii. Local Mapping based on our large dataset is perfect to modify the local shape of the calf and thigh.

3) Our method has shown its advantage over the state-of-art one. But we still want to know if the size of the dataset influence the result of our method. Thus we compare the results of Local Mapping based on the previous and our large datasets in Figure 12. As chest circumference is increased, the height of whole body is changed if the mapping is learned from the small dataset while the results based on the large dataset has no change of body height. We conclude that although Local Mapping has more power to represent semantic changes, it still requires a large dataset to perform optimally.

4) Though results of Global Mapping and Local Mapping learned from our large dataset are visually similar in some cases, changing parameters of some parts will still affect nonadjacent parts in the results of Global Mapping , e.g., when we adjust the thigh circumference, the chest part

	TC	CC	FL	UAL	CC1	CC2	WC1	WC2
Average Offset of Global Mapping(cm)	0.70	5.04	-0.39	-0.10	0.65	0.46	-0.12	-0.10
Average Offset of Local Mapping(cm)	0.04	5.02	0	0	0	0	0	0.01

Table II

DETAILED SEMANTIC PARAMETER ANALYSIS. TC: THIGH CIRCUMFERENCE; CC: CALF CIRCUMFERENCE; FL: FOREARM LENGTH; UAL: UPPER ARM LENGTH; CC1: BREADTH OF CHEST CIRCUMFERENCE; CC2: THICKNESS OF CHEST CIRCUMFERENCE; WC1: BREADTH OF WAIST CIRCUMFERENCE; WC2: THICKNESS OF WAIST CIRCUMFERENCE. NOTE THAT CHANGES IN ONE SEMANTIC PARAMETER OVERFLOW INTO OTHER PARAMETERS WHEN GLOBAL MAPPING IS USED. THE LOCAL MAPPING INTRODUCED IN THIS PAPER GREATLY REDUCES THIS EFFECT.

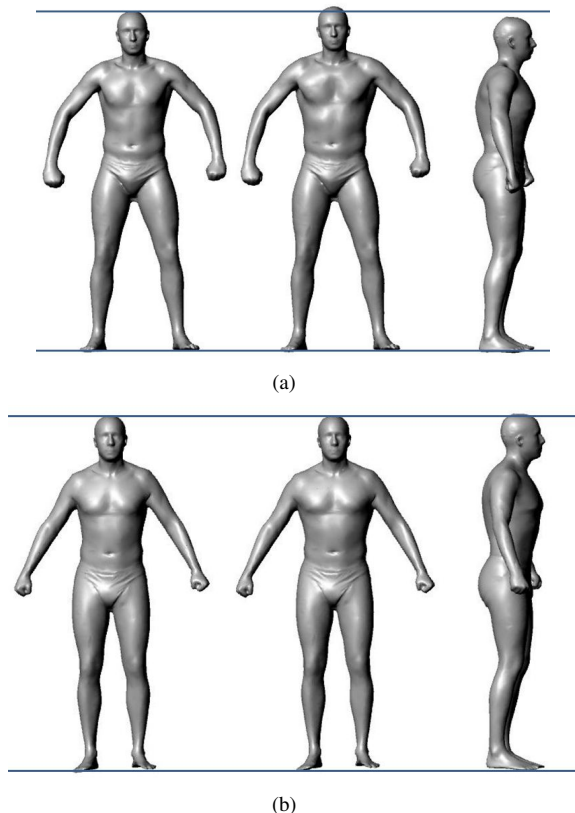


Figure 12. Results comparison: chest circumference is increased. The results of local mapping using the previous (a) and our large (b) datasets are shown. In each subimage, the template (left), results of adjustment of chest circumference breadth (middle) and thickness (right) are shown.

also changes. We made a quantitative comparison between Local Mapping and Global Mapping methods to show these differences. We increase the calf circumference by 5cm and generate the corresponding mesh using Global Mapping and Local Mapping. Then we measure the semantic parameters of the generated mesh. Table II shows the results. The Local Mapping method has less influence on nonadjacent parts than Global Mapping when we adjust this parameter. This matches the results previously shown visually and we observe similar quantitative results with other parts. This implies that the proposed Local Mapping method outperforms the Global Mapping method in terms of accuracy and ability to change semantic parameters individually.

VI. CONCLUSION

In this paper, we introduce Semantic Parametric Reshaping (SPRING), a linear regression model to explore the space of detailed semantic parameters. We compare the results of our *local* regression method with the state-of-art *global* method, and conclude our local modeling better preserves independence among parameters, especially for smaller datasets.

One avenue of future work is to consider how a large dataset might influence other portions of the modeling pipeline. For example, in our regression model, the semantic parameters influencing each rigid part are defined manually. However, given a dataset of 3,000+ body meshes, an automated method may be possible to determine which semantic parameters should be included for each rigid part.

Semantic models such as the one presented here, allow applications that are difficult using global PCA based models. For example, consider virtual garment fitting, modeling and design [18]. If a consumer provides measured body parameters, a semantic model allows an approximate body mesh to be generated for use by tailors and customization design tools.

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