

Generating Statistically Plausible Body Shape Variations for Perception Studies

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Abstract

We present a novel method for morphing 3D body scans according to semantic constraints for generating realistic variations of existing body shapes. By non-linearly optimizing the body shape in a statistical shape space, we ensure that user defined constraints are fulfilled while the main characteristics of a body are still maintained. We demonstrate the quality of the proposed algorithm on various real world use cases.

1 Introduction

Visualizing realistic variations of humans is important in various applications, ranging from perception studies (e.g., assessing the influence of waist-hip ratio (WHR) on attractiveness) to the simulation of weight loss as a motivation tool. Perception studies usually work with 2D drawings or photographs showing different versions of one stimulus. They either show different persons, or they show digitally altered variants of one person. Unfortunately, both approaches have significant drawbacks. On one hand, it is hard to validate that digital alterations are realistic or statistically plausible. On the other hand, it is impossible to vary only one stimulus when working with photos of different persons – which may falsify results if multiple stimuli are correlated. To alleviate those shortcomings, we propose to work with 3D scans instead of 2D images and to alter those scans based on a statistical model.

Previous Work: The concept of morphable three-dimensional models (statistical shape spaces) was first introduced by Blanz and Vetter (1999) for 3D face scans. They also present a method for morphing 3D face scans according to semantic (facial attributes) constraints, but formulate the problem via linear regression. Allen et al. (2003) later extended the method to human body scans. The SCAPE model (Anguelov et al. 2005) decouples shape and pose of human body scans by working in on triangle deformation gradients and estimating

separate deformations for identity (shape) and posture. Hasler et al. (2009) encoded the shapes differently in order to make the statistical model more robust w.r.t. pose variations.

2 Proposed Method

Statistical Model and Data Preparation: Our method starts with building a statistical model of body shapes based on 3D scans of the desired target population. To build the statistical model, we closely follow the approach proposed by Blanz and Vetter (1999) and Allen et al. (2003): First, we fit a common template mesh to each input scan using non-rigid registration based on the LARAP deformation energy (Zollhoefer et al. 2012), which provides us a common topology for all input scans. To compensate for pose variations in the input scans, we apply the pose normalization proposed by Colaianni et al. (2015). We finally perform principal component analysis on the pose normalized scans to obtain our shape space defined by an average body model and its principal components (See Figure 1).

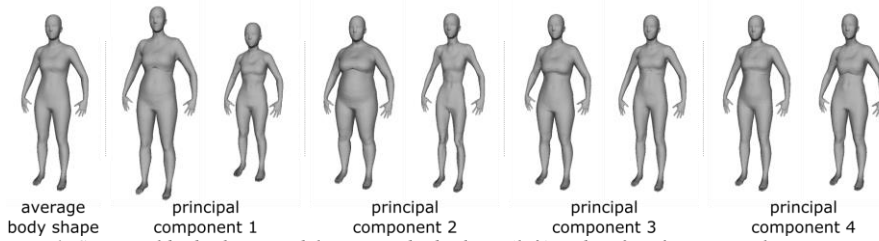


Figure 1: Statistical body shape model: average body shape (left) and its first four principle components. To visualize the principal components, we morph the average body shape $\pm 3\sigma$ units in the respective directions.

Semantic Morphing in Shape Space: Given a three-dimensional body scan, we morph that scan according to user defined semantic constraints as shown in Figure 2: First, we apply non-rigid registration to fit our template mesh to the input scan (a). Since the template contains significantly fewer vertices than standard body scans, the registration generally leads to a loss of data. For being able to reconstruct the lost information at a later stage, we store fine scale detail by computing the closest point on the corresponding avatar (defined as barycentric coordinates w.r.t. the closest triangle) for each vertex of the input scan. Next, we apply a pose normalization to the avatar (b). The pose normalized avatar is then projected into shape space, i.e., the coefficients $\{c_i\}$ of the avatar inside the space spanned by the statistical model are estimated (c). Subsequently, we apply our novel non-linear optimization technique for synthesizing the avatar (described by shape space coefficients $\{\hat{c}_i\}$) which is most similar to our input avatar while fullfilling the user defined semantic constraints. More specifically, we use the Levenberg-Marquardt (LM) algorithm to minimize our objective function $E(\{\hat{c}_i\})$, where E is defined as

$$E(\{\hat{c}_i\}) = 0.005 \sum_i (c_i - \hat{c}_i)^2 + (cons_{current}(\{\hat{c}_i\}) - cons_{target})^2$$

and $cons_{current}(\{\hat{c}_i\})$ is the one (or multiple) target parameter for which we curently optimize the body shape (e.g., the Body Mass Index (BMI)). Our implementation of the LM

algorithm is based on numeric derivatives of the target function. Hence, during each evaluation of the target function $E(\{\hat{c}_i\})$, we explicitly reconstruct the body shape defined by the current parameter set $\{\hat{c}_i\}$ and compute the required measurements (e.g., height and weight for BMI) from that body shape. The set of coefficients $\{\hat{c}_i\}$ minimizing our objective function E is finally used to reconstruct the morphed avatar – which now exactly satisfies the user constraints while still being as close as possible to the initial shape (according to the metric introduced by our shape space). The next step then re-applies the pose of the input scan to our morphed avatar (e). Finally, fine scale detail is recovered (f). Therefore, we compute for each triangle fan in the avatar mesh (after step (a)) the affine transformation which maps the fan onto the corresponding triangle fan of the triangle mesh after pose reconstruction. Each vertex of the input scan is ultimately warped by applying the average (according to the barycentric coordinates computed in step (a)) affine transformation of its closest point on the avatar mesh, which gives us the final morphed scan.

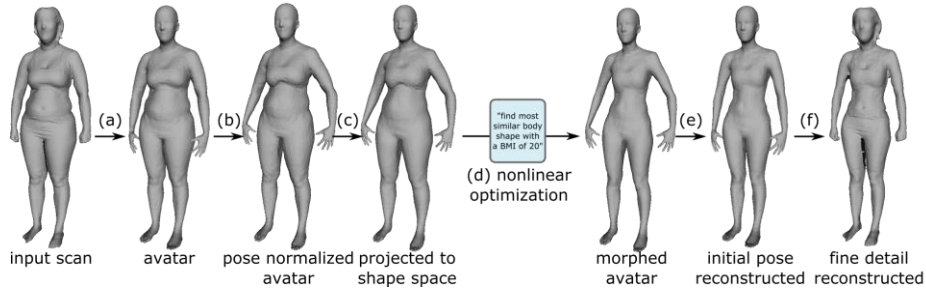
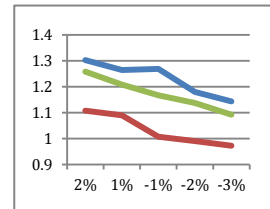


Figure 2: Workflow for morphing a 3D body scan according to user defined semantic constraints.

3 Results

We applied the proposed method to weight loss prediction and waist-hip ratio manipulation, using a statistical model built from 98 body scans of females between 18 and 70 years. The results for three individuals are shown in Figure 3. Note how well the created morphs preserve the characteristics of the input body shape. The leftmost example shows that photorealistic results can be obtained when morphing 3D scans acquired by photogrammetry.

To test whether our approach behaves differently from the current state-of-the-art semantic morphing based on linear regression, we created various morphs for three test persons with different target waist-hip ratios (e.g., we changed their initial WHR by +2%, +1%, -1%, -2%, -3%). Analyzing the shape space differences (i.e., the differences between the two coefficient vectors) between the input scans and their morphed counterparts shows that those are clearly not similar across the different morphs. Note that this would be the case for morphing based on linear regression. This is also depicted in the inset graph on the right, where we plot the change in the ratio between the second and the fourth principal component (those two exhibit the strongest response for WHR changes) for three individuals.



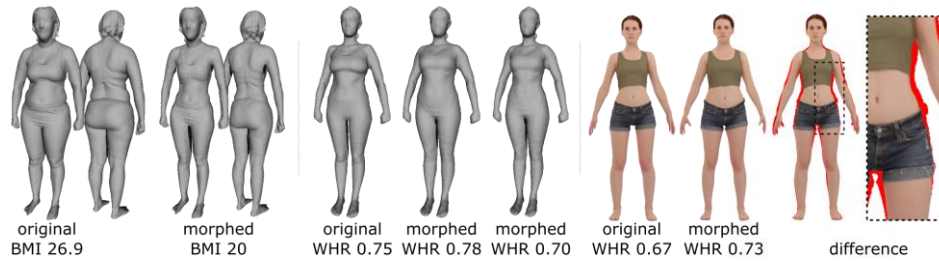


Figure 3: Weight loss simulation (left) and manipulation of the Hip Waist Ratio (WHR) of a photorealistic 3D body scan (right) and a 3D scan acquired by a standard laser scanner (middle).

4 Conclusion and Future Work

We presented a novel method for morphing 3D body scans according to semantic constraints using non-linear optimization in shape space. Our technique creates very realistic morphs that preserve the main characteristics of a body and at the same time exactly fulfill the given constraints. Early results indicate that our technique outperforms previous algorithms based on linear regression morphing. In future, we plan to have a closer look the difference between state of the art algorithms and ours. This could be done by morphing a set of 3D scans according to some constraints (e.g., BMI) and then assessing the quality of the algorithms (measuring how well the results satisfy the target constraints and how similar the initial scan and the created morph are – which should be assessed by an A/B test). In addition, we plan to implement a fitness training software that will be used to evaluate the applicability of the method for the simulation of weight loss and its influence on user motivation.

Literature

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