Avatar Reshaping and Automatic Rigging Using a Deformable Model

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Figure 1: *Our avatar generation system allows the user to reshape and resize an input body scan according to human proportions. The reshaped scans are then automatically rigged into skinned virtual characters, which can be animated in an interactive virtual environment.*

Abstract

3D scans of human figures have become widely available through online marketplaces and have become relatively easy to acquire using commodity scanning hardware. In addition to static uses of such 3D models, such as 3D printed figurines or rendered 3D still imagery, there are numerous uses for an animated 3D character that uses such 3D scan data. In order to effectively use such models as dynamic 3D characters, the models must be properly rigged before they are animated. In this work, we demonstrate a method to automatically rig a 3D mesh by matching a set of morphable models against the 3D scan. Once the morphable model has been matched against the 3D scan, the skeleton position and skinning attributes are then copied, resulting in a skinning and rigging that is similar in quality to the original hand-rigged model. In addition, the use of a morphable model allows us to reshape and resize the 3D scan according to approximate human proportions. Thus, a human 3D scan can be modified to be taller, shorter, fatter or skinnier. Such manipulations of the 3D scan are useful both for social science research, as well as for visualization for applications such as fitness, body image, plastic surgery and the like.

CR Categories: I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—Radiosity; I.4.3 [Computer Graphics]: Three-Dimensional Graphics and Realism—Enhancement

Keywords: rigging, 3d scanning, deformable model, SCAPE

1 Introduction

Recent advances in scanning technology and methods have enabled the acquisition of human models through a variety of photogrammetry methods using RGB cameras, as well as through the use of commodity RGB-D sensors, such as the Microsoft Kinect. Such human 3D models can be used as static imagery in a 3D simulation or as a printed model [Li et al. 2013]. However, the use of such 3D models as dynamic 3D characters requires additional efforts to properly rig the model in order to provide the control mechanism and deformation behavior. Since a human subject 3D scan can contain a high level of detail, improper rigging caused by bad bone positioning can cause deformation artifacts which are relatively easy to see on such models. This is in contrast with cartoony or stylized models where such detail is can be hidden by the resolution or style of the 3D model. Thus, high quality rigging is necessary for 3D human scans.

There is a class of 3D applications or simulations that would benefit from a just-in-time acquisition of a 3D animated character from a human scan. Such applications or simulations would likewise require a rapid and accurate rigging. In this work, we demonstrate the use of a 3D human model database to generate a morphable model to automatically fit a 3D human scan. Once our morphable model is constructed to fit the 3D human scan, we demonstrate the transfer of attributes from the model onto the scan. Thus, we can transfer

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the location of skeletal bones, as well as the skinning deformation information. The quality of the skinning and bone location is of similar quality to that of the original rigging information, that can be performed once by a professional 3D rigger. This is in contrast to a number of other automatic rigging methods that either rely on the geometry to determine the skeletal location, or necessitate multiple example meshes for input.

In addition to transferring the bone location and skinning information, our morphable model allows us to modify the physical attributes of our 3D human scan, such as height, weight, or other physical features. The physical attributes change with human proportions that are captured in the human model database, allowing us to model the effects of getting fatter, thinner, taller, shorter and so forth. Such modifications could be useful for fitness visualization, plastic surgery visualization, avatar enhancement such as adding height or muscularity, and so forth. Such reshaping has been demonstrated on 2D images [Zhou et al. 2010] or videos [Jain et al. 2010] using manual annotation, while ours works on 3D models automatically without annotations.

2 Related Work

2.1 3D Avatar Generations From 3D Scans

3D shape reconstruction has been extensively explored, among which the 3D shape reconstruction of human subjects is of specific interest to computer vision and computer graphics, with its potential applications in recognition, animation and apparel design. With the availability of low-cost 3D cameras (eg, Kinect, RealSense, and StructureSensor), many inexpensive solutions for 3D human shape acquisition have been proposed. The work by [Tong et al. 2012] employs three Kinect devices and a turntable and the work done in [Zeng et al. 2013] utilizes two Kinect sensors in front of the self-turning subject. More recently, solutions which utilize only a single 3D sensor have been proposed, and this allows for home-based scanning and applications. The works in [Wang et al. 2012; Cui et al. 2013; Li et al. 2013] asks the subject to turn in front of a fixed 3D sensor, and multiple key poses are captured and then aligned in a multi-view non-rigid manner to generate the final model. All these works capture the static geometry of human subjects, and additional efforts are necessary to convert the static geometry into an animated virtual character.

The research works in [Wu et al. 2013; Vlasic et al. 2009] focus on capturing the dynamic shapes of an actor's full body performance. The capturing sessions usually require a dedicated setup with multiple cameras and are more expensive than capturing only the static geometry. The resulting dynamic geometries can be played back to produce the animations of the scanned actor. Instead of playing back the captured mesh sequences, the work by [Shapiro et al. 2014] demonstrates a process of scanning human subjects and automatically generate 3D virtual characters from the acquired static 3D models via automatic rigging. The users can then control and animate their own 3D figures in a simulated environment within minutes with animation retargeting [Feng et al. 2013]. The goal of our work aligns with this method to rapidly produce a 3D avatar. However, we focus on adding the reshaping capability and improving the auto-rigging quality in the automatic avatar generation pipelines.

2.2 Morphable Human Models

Recent advances in 3D scanning and analysis of human body shape space help produce the morphable human models we utilize in this work. The pioneering work by Allen et al [Allen et al. 2003] fits a template mesh onto a database of 3D human body scans to build a set of body shape meshes with consistent topology. Such sets of consistent meshes provide an easy way to analyze the human body shape space via standard methods such as pricipal component analysis (PCA). Therefore it is straightforward to morph a human model into various sizes and proportions by adjusting such properties in body shape space. More recently, other methods try to extend the analysis to pose-dependent deformations by encoding various body shape deformations due to both different identities and poses [Anguelov et al. 2005; Hasler et al. 2009a; Allen et al. 2006]. These works result in a morphable human model that can be used to easily generate a human body shape of any identities and poses.

Such morphable models can be used for many applications such as reshaping human bodies in still images [Zhou et al. 2010] or videos [Jain et al. 2010], completing a partial 3D body scan with holes [Weiss et al. 2011], or estimating the 3D body shapes under clothing [Hasler et al. 2009b], or creating 2D imagery in real time from RGB-D scans [Richter et al. 2012]. In our work, we apply the SCAPE method [Anguelov et al. 2005] to build a morphable model, and then use it for building mesh correspondences and reshaping existing 3D human scans.

The commercial system BodyHub [Inc. 2015] allows the construction of a 3D model using measurements of a 3D scan. Our work differs in that we are interested in preserving the original model and detail, such as textures. By contrast, BodyHub discards the original scan data in favor of a 3D model that represents the approximate shape and size of the original scan. Thus, the scan data is merely used as an entry point to generate a 3D model from a template.

2.3 Automatic Rigging

Although it is relatively easy to obtain static 3D character models through 3D scanning, it requires additional effort to create an animated virtual character. A 3D model needs to be rigged with a skeleton hierarchy and appropriate skinning weights. Traditionally, this process needs to be done manually and is time consuming even for an experienced animator. An automatic skinning method called Pinocchio is proposed in [Baran and Popović 2007] to reduce the manual efforts of rigging a 3D model. The method produces reasonable results but requires a connected and watertight mesh to work. The method proposed in [Shapiro et al. 2014] first voxelizes the mesh to remove all topological artifacts and solve for 3D skeleton in voxel space. Therefore it can work on generic models that are created by 3D artists. The method proposed by [Bharaj et al. 2011] complements the previous work by automatically skinning a multi-component mesh. It works by detecting the boundaries between disconnected components to find potential joints. Thus the method is suitable for rigging the mechanical characters that usually consist of many components. The work by [Jacobson et al. 2011] can be used to produce smooth blending weights with intuitive deformations. However, their method does not provide a mechanism to automatically generate the skeletal rig. Other rigging algorithms can include manual annotation to identify important structures such as wrists, knees and neck [Mix 2013]. Some autorigging methods require a mesh sequence [Le and Deng 2014; Wang et al. 2007]. By contrast, we are performing a automatic rigging with only a single mesh. The work in [Ali-Hamadi et al. 2013] proposed a semi-automatic pipeline to transfer the full anatomy structure from a source model to a target model. Their method requires both models to share the same (u, v) texture space and does not provide the reshaping capability for the resulting model. Our method of autorigging has similarities with the work in [Miller et al. 2010], which demonstrated the use of rigged body parts which were then assembled into the full skeleton. We likewise rely on a pre-rigged template. However, our method requires only a single rig to be defined, rather than a set of rigs to be matched from a rig database.

In our work, we utilize the SCAPE model to fit a input human body scan and then automatically rig the input scan by transferring the high quality rigging from SCAPE model. Although our method is limited to the 3D scans from human bodies, it produces superior skinning results compared to other generic auto-rigging methods such as Pinocchio [Baran and Popović 2007]. Since the input scan has a photorealistic quality and high levels of detail, an accurate rigging is needed to properly animate the resulting character. Poor quality rigging can result in distracting artifacts which can be in-obvious on cartoony or stylized models that contain large areas of nondescript surfaces, such as pants or shirts that lack folds, but are often distracting on models that have high levels of detail, such as those derived from scans of human subjects. Thus methods that provide approximate bone positions based on geometry surfaces and shapes [Pan et al. 2009] are often not sufficient for animation of photorealistic characters.

3 System Overview

Our goal is to develop a virtual avatar generation system based on an input 3D body scan. Our system has two main capabilities; (1) automatic rigging transfer, and (2) interactive avatar reshaping. Figure 2 summarizes the stages in our avatar generation pipeline. We start by utilizing SCAPE [Anguelov et al. 2005] to build a morphable human model from a 3D human model database (Section 4.1). In order to allow pose deformations via linear blend skinning, we also manually rigged a template mesh from the database. Therefore given a 3D human body scan, we can fit the morphable human model produced by SCAPE onto the input scan and establish mesh correspondences between them (Section 4.3).

Once we establish such correspondences, they can be used to transfer both skeleton and skin binding weights from the template mesh onto the input scan to generate a 3D virtual avatar (Section 5.2). The user can also interactively adjust semantic body attributes of the fitted model by exploring body shape space generated from the database. Such body shape deformations can then be transferred to the aforementioned 3D scan to further create various virtual avatars with different body sizes and proportions (Section 5.1). The resulting virtual avatars can then be animated in a simulation environment to execute various behaviors using animation retargeting.

4 Morphable Model Fitting

Our goal is to establish correspondences between a 3D body scan and the morphable human models. Such correspondences would allow us to utilize the body shape database to effectively transfer both body shape deformation as well as rigging information from morphable models to a body scan. In this section, we present the technical details about building the morphable models and how to automatically fit such models to a body scan.

4.1 3D Morphable Human Model

We use a simplified version of SCAPE [Anguelov et al. 2005] method to create a morphable human model with both pose and body shape variations. The input is a rigged template mesh and a database of 3D human models. We use the body model database provided in [Yang et al. 2014] to build the morphable model. The template mesh is defined as $X = \{V, P, B\}$ with $|V|$ vertices, $|P|$ triangles and $|B|$ joints where $V = \{v_1, \ldots v_{|V|}\}$, $P = \{p_1, \ldots p_{n_{|P|}}\}$ and $B = \{b_1, \ldots b_{|B|}\}$. Each vertex v_i in X also corresponds to a set of skin binding weights $w(v_i) = \{w^1(v_i), \ldots w^{|B|}(v_i)\}$ that will be used for linear blend skinning. The database of 3D human models are defined as $U = U^1 \ldots U^N$

where $U^i = \{u_1^i, \ldots u_{|V|}^i\}$ are vertex positions of i-th shape. The SCAPE model can then be built from the body mesh database by learning a set of parameters for both pose and shape dependent deformations. Unlike in the original SCAPE model, we use traditional linear blend skinning to directly compute the pose-dependent deformations caused by skeletal poses θ. This simplifies the process of model fitting later and results in faster pose optimization. On the other hand, the shape-dependent deformations $S_k(\beta)$ is the per-triangle transformation caused by different body shape parameters β. Here θ is the concatenation of all joint angles in the skeleton and β^i for each shape U^i is the coefficient vector corresponding to the data point in a low-dimensional shape space constructed by principal component analysis (PCA). Together they can be used to produce a new body mesh M based on input parameters (θ, β). This can be done by first solving the Poisson equation, which minimize

$$\arg \min_{V'} \sum_k^{P|} \|S_k(\beta)\nabla p_k - \nabla p_k'\|^2 \tag{1}$$

to obtain a subject specific body shape V' based on β, where ∇p_k and $\nabla p_k'$ is the per-triangle deformation gradient for V and V', respectively. Then the pose dependent deformation can be obtained via linear blend skinning

$$T(\theta, v_i) = \sum_l^{|B|} w^l(v_i) R_l(\theta) v_i \tag{2}$$

where $R_l(\theta)$ is the global bone transformation of joint b_l computed using skeletal hierarchy and joint angles θ. In the following section, we denote

$$M(\theta, \beta) = T(\theta, V'(\beta)) \tag{3}$$

as a morphable model that can represent the 3D human geometry of different body shapes and in different poses.

4.2 Skeleton Morphing

Since one of our goals is to transfer the rigging from the morphable model to a target body scan, the underlying skeleton also needs to be adjusted to body shape variations by finding new skeletal joint placements given a new β. However, it is not a trivial task to find a new location for each joint, since the new mesh can have various changes in height, size, and limb lengths. In order to have joint locations changed continuously according to shape parameters, we choose to represent joint locations as linear combinations of mesh vertex positions. Specifically, we compute the mean-value coordinates (MVC) [Ju et al. 2005] $m^j(V)$ for each joint $b_j, j = 1 \ldots |B|$ in the rigged template mesh X as

$$b_j = \sum_i m^j(v_i) v_i \tag{4}$$

, where $m^j(v_i)$ is the mean-value coordinates of v_i for joint b_j. Thus as shape parameters change, we can use vertex positions v_i' from the newly reconstructed body shape V' to infer new joint locations.

Figure 3 demonstrates skeleton morphing results for SCAPE models under different shape parameters.

4.3 Body Shape and Pose Optimization

Once we have a morphable human model, the next task is to fit the model $M(\theta, \beta)$ to a 3D body scan $Y = \{Z, F\}$ with vertices $Z = z_1, \ldots z_{|Z|}$ and triangles $F = f_1, \ldots f_{|F|}$. The fitting is done by optimizing both θ and β such that the resulting M becomes a
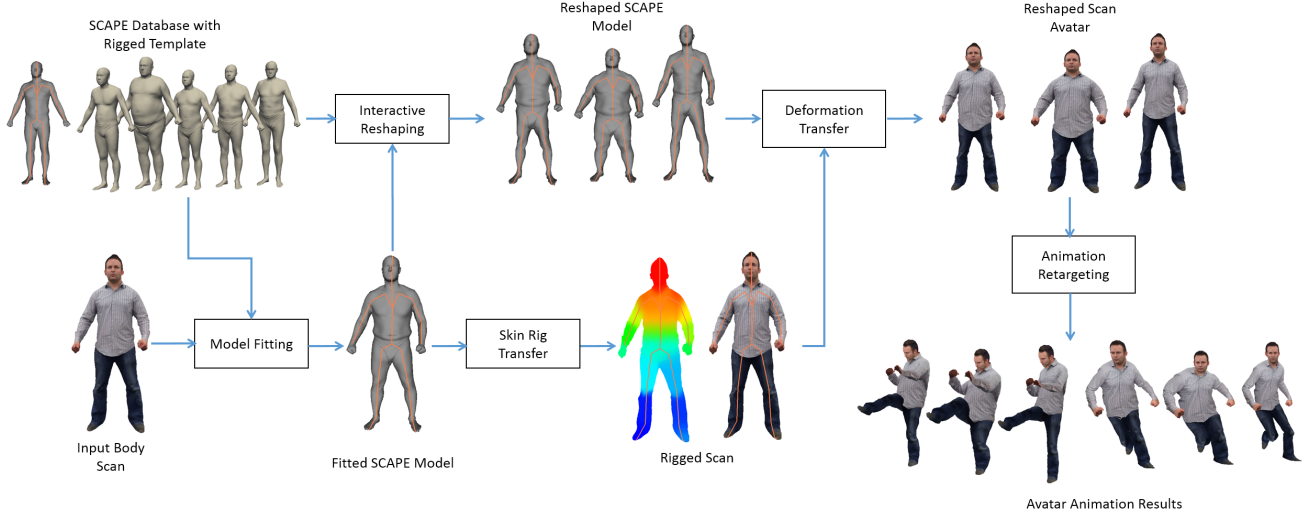
Figure 2: *Overview of our avatar reshaping and rigging system.*
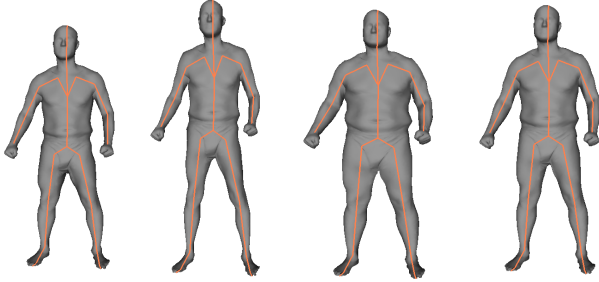

Figure 3: *SCAPE models with different shape parameters. Note that the corresponding skeleton for each model is also morphed to fit the new shape.*

good approximation for Y. We use a optimization strategy similar to iterative closest point (ICP) by first finding suitable vertex pairs between M and Z and then deforming M to match corresponding vertex positions in Z. Since the two models tend to have different initial poses, we need to find a good initial estimation of skeletal pose θ^{init} for M before running the optimization. Our solution is to extract a skeleton B' from the input mesh Y using a variation of Pinocchio automatic rigging method proposed in [Shapiro et al. 2014] and use B' to determine θ^{init}. Although B' is not an accurate skeletal representation and can not be used as the final rigging for Y, we can use it to infer the initial θ^{init} by hierarchically rotating each joint b_j in B to match corresponding the bone orientation of b'_j in B' [Feng et al. 2013]. Moreover, we need to find a good set of vertex pairs between two meshes at each iteration in order to solve for (θ, β). However, due to the fact that the human form contains complicated and varying shapes, a naive nearest neighbor strategy tends to result in incorrect correspondences especially in the region close to arms and chests. To alleviate this issue, we apply the strategy that finds the nearest compatible points between two meshes and use those points to find vertex pairs.

Let $C = \{(a_1, b_1), \dots (a_{|C|}, b_{|C|})\}$ be the vertex index pairs obtained at the beginning of each iteration. In order to avoid the solution to be trapped in a local minimum, we adapt the strategy pro-

posed in [Masuda et al. 1996] to randomly select only one-tenth of all point pairs into C. Our optimization problem can then be formulated as follows :

$$\arg \min_{\theta, \beta} \sum_{(a,b) \in C} \|T(\theta, v'_a(\beta)) - z_b\|^2 \tag{5}$$

where $v'_a(\beta)$ is the vertex corresponding to index a in V' after solving equation 1. Equation 5 forms a non-linear least square problem, and we solve it using the Ceres solver [Agarwal and Mierle 2012]. At each iteration, we solve for (θ, β) based on the current set of vertex correspondences. To improve the optimization efficiency and the overall fitting results, we solve θ and β separately in an alternating manner during the optimization. After each iteration, a new set of vertex correspondences between M' and Z are computed under the new mesh deformations defined by (θ, β). The above process is repeated until the least square error defined in equation 5 is smaller than a threshold or when the maximum number of iterations is reached. We denote (θ', β') as the resulting parameters after optimization and will use the morphable model $M' = M(\theta', \beta')$ as the approximation of Y in the next section to establish correspondences between them. Such correspondences will be used in the following sections for transferring the reshaping deformations and skin rigs. Figure 4 shows the morphable model approximation after parameter optimization and the resulting skin rig after skin transfer (Section 5.2).

5 3D Avatar Reshaping and Automatic Rigging

We can use the resulting morphable model approximation from the previous section to establish mesh correspondences. Such correspondence will be used to both guide the body shape deformations as well as transfer the rigging for Y. Specifically, we use morphable model M' as the source mesh and the input 3D body scan Y as target mesh and apply deformation transfer [Sumner and Popović 2004] to reshape Y. On the other hand, high quality skinning rig transfer is achieved through both mean-value coordinates and harmonic interpolation.
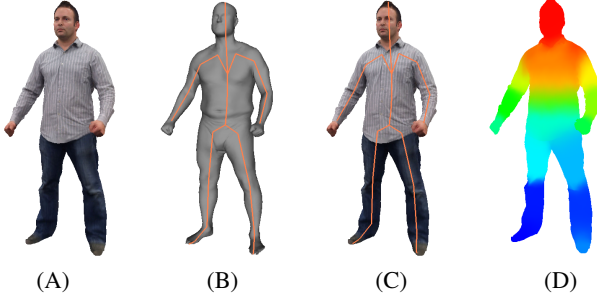
(A) (B) (C) (D)

Figure 4: *The model fitting process starts at an input body scan (A). The system then performs body and pose optimization to adjust the SCAPE parameters and produce an approximate model (B). The new skeleton (C) for the body scan can then be computed by transferring mean-value coordinates. Finally, the new smooth skin weights (D) can be computed using harmonic interpolation.*
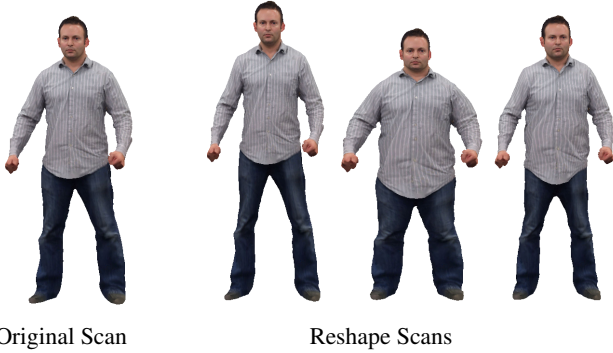

Original Scan Reshape Scans

Figure 5: *(Left) Original Scan (Right) Novel body models after reshaping. Our system reshapes the original body scan into various different body shapes while reasonably preserving human body sizes and proportions according to the human model database.*

5.1 Deformation Transfer

We can adjust M' with a new shape parameter β^* such that $M^* = M(\theta', \beta^*)$. Since the shape parameters β^* are PCA coefficient vectors, they do not represent any meaningful semantic body features such as weight, height, and so forth. In order to allow more intuitive control over body reshaping, we follow the method in [Allen et al. 2003] and compute a linear regression $f(\gamma) = \beta$ where from the shape database to build a mapping from semantic feature γ to β. Thus the new shape parameters can be defined as $\beta^* = \beta' + f(\Delta\gamma)$ to specify the changes in semantic attributes from M'. Once the user provides a new β^* via interactive control, we can compute the per-triangle deformation gradient S_k^* using M' as the undeformed mesh and M^* as the deformed mesh. Once we obtain S_k^* that encodes the body shape deformations due to $\beta*^*$, we can transfer such deformations to Y. First, we compute the triangle correspondences between M' and Y by finding all closest compatible triangle pairs. Such correspondences can be then be used to map each S_k^* for p_k to a matching triangle in Y. A new deformed vertex positions Z^* can then be computed by solving the same Poisson equation as in Equation 1. Figure 5 and 7 demonstrates some examples of reshaping the original scan into human models with different body sizes and proportions.

5.2 Skinning Rig Transfer

The mesh correspondence also helps us transferring the high quality rigging associated from morphable model M' to input 3D body scan Y. To achieve this, we need to infer both skeletal joint placements $B^Y = \{b_1^Y, \dots b_{|B|}^Y\}$ and skin binding weights $w(z_i)\{w^1(z_i), \dots, w^{|B|}(z_i)\}$ for each vertex z_i in Y based on the rigging provided by M'.

In order to transfer the skeleton, an intuitive solution is to make use of the joint positions from the morphed skeleton B' corresponding to M' by copying over joint positions to form B^Y. However, since M' is not an exact fit for the scan mesh Y, the resulting joint placements may not be ideal. Thus instead of explicitly transferring the joint positions, we choose to transfer the mean-value coordinates from M' to Z and implicitly use them to infer the new joint placements. Specifically, for each vertex z_i in Y, we compute its MVC mz_i^j for b_j from M' as

$$ m^j(z_i) = \frac{A(z_i)}{A(Z)} \sum_{k \in p_{z_i}} \lambda^k(z_i) m^j(v_k) \qquad (6) $$

where $A(z_i)$ is the vertex area of z_i, p_{zi} is the closest triangle in M' from z_i, and $\lambda^k(z_i)$ is the barycentric coordinate after projecting z_i onto p_{zi}. The above formula computes an interpolated mean-value coordinates for each z_i by projecting it onto nearby triangle in M'. Since $\sum_{i=1}^{|Z|} m^j(z_i) = 1$, we normalize $m^j(z_i)$ after the finding all of the MVCs for Z to find the final values. Thus the resulting $m^j(z_i)$ can be used in the same way like $m^j(v_i)$ to find B^Z by following equation 4. Moreover, since B^Z is represented as a linear combination of vertices Z in Y, a new morphed skeleton B^{Z^*} can be easily recomputed using the same equation with new vertex positions from Z^*. This allows a quick and accurate update of skeleton joint placements during interactive reshaping session.

To compute the skin binding weights $w(z_i)$, we can follow a similar interpolation scheme by projecting each vertex z_i onto nearby triangle and using barycentric coordinate interpolate the skin weights $w(v_k)$ where $k \in p_{z_i}$ from the nearby triangle p_{z_i}. For a low resolution mesh where $|Z| < |V|$, such method would suffice. However, the input high resolution 3D body scan tends to have more than 100K vertices while our morphable model has much lower resolution of about 10K vertices. Therefore simply projecting each vertex z_i usually produces in non-smooth skin weights and results in various artifacts during run-time skin deformations. To alleviate such problem, we apply harmonic interpolation over the mesh Z [Zayer et al. 2005] to produce skin weights wz_i that are both smooth and faithful to original skinning weights. We start by finding $C^{M'} = \{(a_1, b_1), \dots (a_{|V|}, b_{|V|})\}$, which is the correspondence vertex index pairs from each vertex in M' to its closest compatible point in Z and set $w(z_b) = w(v_a)$ for each vertex index pair (a, b). This will produce the skin weights for a subset of vertices in Z. The rest of skin weights can then be interpolated by solving Laplace equation :

$$ Lh = 0 \qquad (7) $$

subject to boundary condition $w(z_b) = w(v_a)$ for all correspondence pairs in $C^{M'}$. Here L is the discrete Laplace-Beltrami operator matrix and h is the resulting harmonic fields that smoothly interpolate skin weights over mesh Z. Figure 6 shows the comparison of transferring skin weights using barycentric coordinates and using harmonic interpolations. The skin weights produced by harmonic interpolation are smoother and result in less skin deformation artifacts.
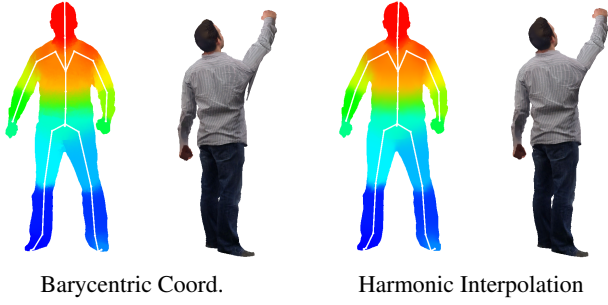
Barycentric Coord.　　　　　Harmonic Interpolation

Figure 6: *Comparison of skin binding weight interpolation schemes. Directly using barycentric coordinates after vertex projection results in non-smooth skin weights and problematic skin deformations. On the other hand, harmonic interpolation produce smoother weights and deformations.*
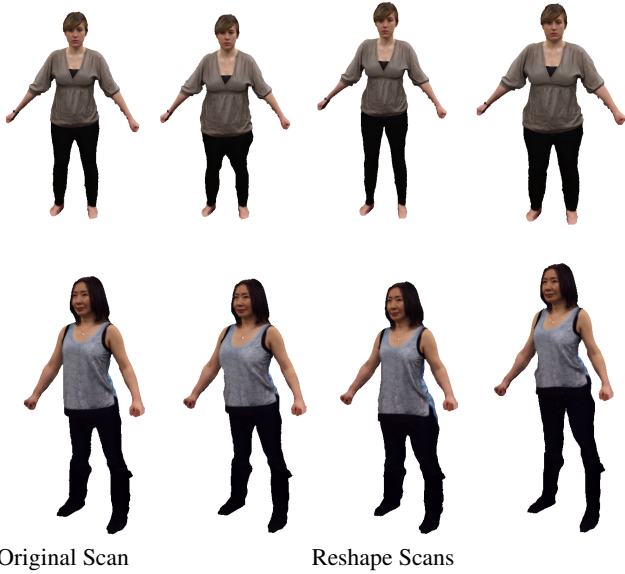

Original Scan　　　　　Reshape Scans

Figure 7: *Additional reshaping results from different subjects. (Left) the original scan, (center and right) scans generated after reshaping. Our system is capable of producing novel body scans for the same subject.*

Rest Pose　　　　　Pinocchio　　　　Our Method

Figure 8: *Comparison of automatic rigging results between our method and Pinocchio [Baran and Popović 2007]. Our method produces superior rigging results with less artifacts and distortions after skin deformations.*

6 Results and applications

6.1 Automatic Rigging and Attribute Transfer

Our method provides a fully automatic way to rig a human-like model with high quality rig. Since we transfer the rig directly from template model to the input body scan, the rigging quality depends on both the correspondence accuracy and original rigging quality. Figure 8 shows the comparison between our automatic rigging method and Pinocchio. Since our method utilizes SCAPE morphable model to find an good correspondences to the input body scan, the skin rig associated with SCAPE model can be transferred to the scan without losing much quality. Thus the virtual avatars generated by our method potentially have more accurate joint placements and skin weights than those generated by automated methods that are based soley on geometric data. Our system is able to process a 3D scan of approximately 100,000 vertices in approximately one minute using an Intel i7 3.3GHz CPU.

Figure 9: *Since the reshaped avatars have different physical body sizes and proportions, the animated results are different when simulated in an virtual environment due to a retargeting algorithm that considers leg length. The avatar with shorter legs runs relatively slower while the tallest avatar outruns others.*

6.2 Avatar Reshaping

Figure 1 and 7 demonstrate some avatar reshaping results generated from our system. Such reshaping is useful for psychological and social science research that involves appearance of self or others. In addition, reshaping is useful for body modification visualization, such as fitness applications that show weight or muscle gain or loss, or plastic surgery visualization. The reshaping can be done at interactive speeds.

We parameterize the human model database by measuring distances between points on the model surface that represent height (top of the head to the ground plane), weight (belly button to back), chest (back to nipple), hip (left to right hip), leg length (top of leg to bottom of foot), and arm length (top of shoulder to palm).

Bodily proportions can affect simulation results for systems that account for such changes in shape. As shown in Figure 9, a locomotion algorithm that takes into account stride length will result in the taller avatar moving faster, while the shorter avatar moves slower.

7 Discussion and Future Work

Limitations Since both our reshaping and automatic rigging schemes requires a body shape database to approximate the input body scan, yhe approximation results are limited by the shape space spanned by models in the database. Although our method does not require a very tight fit to the original scan for reshaping since we utilize deformation gradients to solve for deformations implicitly, the model fitting may be inaccurate if the scanned subject is wearing excessive clothing. Thus the subsequent reshaping results would become unnatural. Currently our method is restricted to rig models that have similar body shapes to a real human. Thus it is not suitable for rigging cartoonish characters created by artists. However, by following similar methodology of rig transfer, we can extend our system to these characters by using additional shapes to span the body shape space of cartoonish characters.

8 Conclusion

Recent advances in scanning technology have enabled widespread acquisition of 3D models from human subjects. In order to use such 3D models for dynamic animation as 3D characters in virtual characters, such 3D static models must be properly rigged. In this paper, we present a method for automatically rigging and skinning of a single 3D human scan by using a human figure database and morphable model. Our system let users interactively reshape and resize the 3D scan according to approximate human proportions. The rigging and skinning attributes can then be transferred to reshaped body scan to produce the virtual avatar. Our rigging results demonstrate superior skin deformation quality compared to previous methods for rigging a single static mesh without examples. We believe our system would be useful both for social science research, as well as for applications in areas such as fitness, body image, or plastic surgery where the visualization of body shape manipulations is important.

References

AGARWAL, S., AND MIERLE, K. 2012. Ceres solver: Tutorial & reference. *Google Inc 2*.

ALI-HAMADI, D., LIU, T., GILLES, B., KAVAN, L., FAURE, F., PALOMBI, O., AND CANI, M.-P. 2013. Anatomy transfer. *ACM Transactions on Graphics (proceedings of ACM SIGGRAPH ASIA) 32*, 6.

ALLEN, B., CURLESS, B., AND POPOVIĆ, Z. 2003. The space of human body shapes: Reconstruction and parameterization from range scans. *ACM Trans. Graph. 22*, 3 (July), 587–594.

ALLEN, B., CURLESS, B., POPOVIĆ, Z., AND HERTZMANN, A. 2006. Learning a correlated model of identity and pose-dependent body shape variation for real-time synthesis. In *Proceedings of the 2006 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, Eurographics Association, Aire-la-Ville, Switzerland, Switzerland, SCA '06, 147–156.

ANGUELOV, D., SRINIVASAN, P., KOLLER, D., THRUN, S., RODGERS, J., AND DAVIS, J. 2005. Scape: shape completion and animation of people. In *ACM Transactions on Graphics (TOG)*, vol. 24, ACM, 408–416.

BARAN, I., AND POPOVIĆ, J. 2007. Automatic rigging and animation of 3d characters. *ACM Trans. Graph. 26*, 3 (July).

BHARAJ, G., THORMÄHLEN, T., SEIDEL, H.-P., AND THEOBALT, C. 2011. Automatically rigging multi-component characters. *Comp. Graph. Forum (Proc. Eurographics 2012) 30*, 2.

CUI, Y., CHANG, W., NÖLL, T., AND STRICKER, D. 2013. Kinectavatar: fully automatic body capture using a single kinect. In *Computer Vision-ACCV 2012 Workshops*, Springer, 133–147.

FENG, A., HUANG, Y., XU, Y., AND SHAPIRO, A. 2013. Fast, automatic character animation pipelines. *Computer Animation and Virtual Worlds*, n/a–n/a.

HASLER, N., STOLL, C., SUNKEL, M., ROSENHAHN, B., AND SEIDEL, H.-P. 2009. A statistical model of human pose and body shape. *Computer Graphics Forum 28*, 2, 337–346.

HASLER, N., STOLL, C., ROSENHAHN, B., THORMHLEN, T., AND SEIDEL, H.-P. 2009. Estimating body shape of dressed humans. *Computers & Graphics 33*, 3, 211 – 216. {IEEE} International Conference on Shape Modelling and Applications 2009.

INC., B., 2015. Bodyhub.

JACOBSON, A., BARAN, I., POPOVIĆ, J., AND SORKINE, O. 2011. Bounded biharmonic weights for real-time deformation. *ACM Transactions on Graphics (proceedings of ACM SIGGRAPH) 30*, 4, 78:1–78:8.

JAIN, A., THORMÄHLEN, T., SEIDEL, H.-P., AND THEOBALT, C. 2010. Moviereshape: Tracking and reshaping of humans in videos. *ACM Trans. Graph. (Proc. SIGGRAPH Asia 2010) 29*, 5.

JU, T., SCHAEFER, S., AND WARREN, J. 2005. Mean value coordinates for closed triangular meshes. *ACM Trans. Graph. 24*, 3 (July), 561–566.

LE, B. H., AND DENG, Z. 2014. Robust and accurate skeletal rigging from mesh sequences. *ACM Trans. Graph. 33*, 4 (July), 84:1–84:10.

LI, H., VOUGA, E., GUDYM, A., LUO, L., BARRON, J. T., AND GUSEV, G. 2013. 3d self-portraits. *ACM Transactions on Graphics (Proceedings SIGGRAPH Asia 2013) 32*, 6 (November).

MASUDA, T., SAKAUE, K., AND YOKOYA, N. 1996. Registration and integration of multiple range images for 3-d model construction. In *Pattern Recognition, 1996., Proceedings of the 13th International Conference on*, vol. 1, 879–883 vol.1.

MILLER, C., ARIKAN, O., AND FUSSELL, D. 2010. Frankenrigs: building character rigs from multiple sources. In *Proceedings of the 2010 ACM SIGGRAPH symposium on Interactive 3D Graphics and Games*, ACM, 31–38.

2013. Mixamo auto-rigger. http://www.mixamo.com/c/auto-rigger.

PAN, J., YANG, X., XIE, X., WILLIS, P., AND ZHANG, J. J. 2009. Automatic rigging for animation characters with 3d silhouette. *Computer Animation and Virtual Worlds 20*, 2-3, 121–131.

RICHTER, M., VARANASI, K., HASLER, N., AND THEOBALT, C. 2012. Real-time reshaping of humans. In *3D Imaging, Modeling, Processing, Visualization and Transmission (3DIMPVT), 2012 Second International Conference on*, IEEE, 340–347.

SHAPIRO, A., FENG, A., WANG, R., LI, H., BOLAS, M., MEDIONI, G., AND SUMA, E. 2014. Rapid avatar capture and simulation using commodity depth sensors. *Computer Animation and Virtual Worlds 25*, 3-4, 201–211.

SUMNER, R. W., AND POPOVIĆ, J. 2004. Deformation transfer for triangle meshes. *ACM Trans. Graph. 23*, 3 (Aug.), 399–405.

TONG, J., ZHOU, J., LIU, L., PAN, Z., AND YAN, H. 2012. Scanning 3d full human bodies using kinects. *Visualization and Computer Graphics, IEEE Transactions on 18*, 4, 643–650.

VLASIC, D., PEERS, P., BARAN, I., DEBEVEC, P., POPOVIC, J., RUSINKIEWICZ, S., AND MATUSIK, W. 2009. Dynamic shape capture using multi-view photometric stereo. In *In ACM Transactions on Graphics*.

WANG, R. Y., PULLI, K., AND POPOVIĆ, J. 2007. Real-time enveloping with rotational regression. *ACM Transactions on Graphics (TOG) 26*, 3, 73.

WANG, R., CHOI, J., AND MEDIONI, G. 2012. Accurate full body scanning from a single fixed 3d camera. In *3D Imaging, Modeling, Processing, Visualization and Transmission (3DIMPVT), 2012 Second International Conference on*, IEEE, 432–439.

WEISS, A., HIRSHBERG, D., AND BLACK, M. J. 2011. Home 3d body scans from noisy image and range data. In *Computer Vision (ICCV), 2011 IEEE International Conference on*, IEEE, 1951–1958.

WU, C., STOLL, C., VALGAERTS, L., AND THEOBALT, C. 2013. On-set performance capture of multiple actors with a stereo camera. In *ACM Transactions on Graphics (Proceedings of SIGGRAPH Asia 2013)*, vol. 32.

YANG, Y., YU, Y., ZHOU, Y., DU, S., DAVIS, J., AND YANG, R. 2014. Semantic parametric reshaping of human body models. In *3D Vision (3DV), 2014 2nd International Conference on*, vol. 2, 41–48.

ZAYER, R., RSSL, C., KARNI, Z., AND SEIDEL, H.-P. 2005. Harmonic guidance for surface deformation. *Computer Graphics Forum 24*, 3, 601–609.

ZENG, M., ZHENG, J., CHENG, X., AND LIU, X. 2013. Templateless quasi-rigid shape modeling with implicit loop-closure. In *Computer Vision and Pattern Recognition (CVPR), 2013 IEEE Conference on*, IEEE, 145–152.

ZHOU, S., FU, H., LIU, L., COHEN-OR, D., AND HAN, X. 2010. Parametric reshaping of human bodies in images. In *ACM SIGGRAPH 2010 Papers*, ACM, New York, NY, USA, SIGGRAPH '10, 126:1–126:10.