Scan2Avatar: Automatic Rigging for 3D Raw Human Scans

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Figure 1: Examples of converting 3D human scan to avatar.

ABSTRACT

A powerful rigging pipeline is proposed to automatically rig the raw scans of human model with 1) fitting a Rigged Parametric Body Model (RPBM) to the scan with a novel and effective energy formulation, 2) cutting the scan to break self-occlusions automatically, 3) inpainting the geometry and texture in UV parametric space to create a complete avatar and 4) transferring the rigging information from the RPBM to the avatar. To further improve the fitting result, Semantic Deformation Component (SDC) is generated and utilized to replace the original shape blendshapes of the RPBM in the fitting stage, which can also be used for body reshaping. Our method is highly effective and robust in rigging the raw human scan models.

CCS CONCEPTS

• **Computing methodologies → Motion processing**.

KEYWORDS

Autorigging, Animation, 3D Digital Human

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1 INTRODUCTION

Advances in 3D scanning technologies is enabling the acquisition of photo-realistic 3D human scans from a set of RGB/RGBD images. Many technology companies, like Microsoft, Intel, Google, Facebook, Samsung and many startup companies, have set up their own multi-view capture studios. Tens of thousands of 3D human models have been scanned. It is expected that the number of human scan models has the potential to grow explosively in the near future. Rigging the scan models and bringing it to life has potential to enable numerous additional downstream AR/MR/VR application, e.g. tele-presence, gaming and etc.

Traditionally, rigging a human model has been done manually with some commercial software (e.g. Maya) which is time-consuming even for animation experts. The existing auto-rigging methods have good performance on artistically designed human models [Baran and Popović 2007]. However, they either have constraints on the mesh size and structure, or only support simple scan poses like T-pose and/or A-pose. A high definition scan model may have millions of vertices without guarantee that mesh is watertight or even connected. Moreover, the scan mesh may contain self-occlusions (e.g. arms on torso, connected legs ect.), and missing regions (e.g. hand in pocket, reconstruction failure etc.). None of the existing methods can resolve them [Adobe [n.d.]; Baran and Popović 2007; Feng et al. 2015].

We propose a fully automatic method to rig 3D raw human scans. To address the complicated geometry of those high-definition raw human scans with self-occlusions, missing regions, and arbitrary outfits, our solution involves transferring the rigging information from a Rigged Parametric Body Model (RPBM) (e.g. SMPLH [Romero et al. 2017]) to the scan and resolve some of the geometry issues in 2D texture space.

2 METHOD

The processing chain of our method is composed of 3 major steps.

- **Step 1–Fitting the RPBM to Scan**
  Given a scanned model, the first step is align the RPBM with it. The RPBM parameterizes the shape and pose-dependent deformations for a naked body. A good alignment is essential for reliable rig transfer and it does not always mean closest surface distance. This is especially true when the input involves varied outfits. Considering the high correlation of 3D joint position with the skeleton, we formulate the fitting energy by combing the Chamfer distance and 3D joint error. The 3D joints of the scanned model are estimated from 2D joints detected from a set of 2D rendered views.
- **Step 2 – Skinning Transfer**
  After the fitting stage, the correspondence between the scanned model and RPBM can be built. For each vertex of the 3D scanned model, we find the closest triangle on RPBM and its barycentric weights. Based on the correspondence, the skinning weight of the scanned model can be calculated.

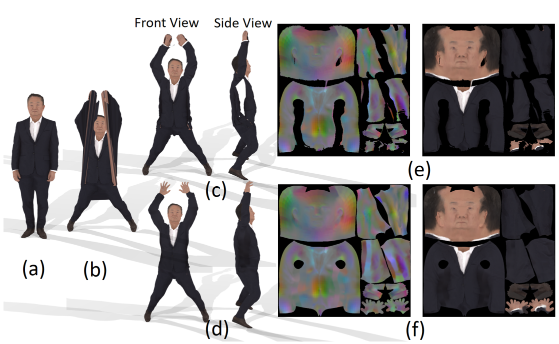

Figure 2: (a) Input 3D scan with arms on torso; (b) Deformed mesh with stretched triangles; (c) Cut 3D mesh with holes on torso and arms; (d) Mesh reconstructed from geometry and color texture; (e) Geometry and texture image before inpainting; (f) Geometry and texture image after inpainting.

- **Step 3 – Geometry and Color Inpainting**
  The given 3D scanned model may contain unwanted connections like connected arm and torso, which will cause stretched triangles (as shown in Fig. 2(b)) when there is relative motion. To resolve the unwanted connections, we cut the stretched triangles automatically based on the body part information, which will create holes on the scanned model. Besides that, the scan model itself may have additional missing regions due to self-occlusions or reconstruction failures. To fill the holes and the missing regions on the input model, we first bake geometry and texture into 2D UV domain, with the geometry texture representing the displacement of the scan *w.r.t* the surface of RPBM, as shown in Fig. 2(e). Then image inpainting techniques are used to fill up both the geometry and texture image with special care to avoid color leaking and smoothness between different charts. After that the final model is reconstructed.

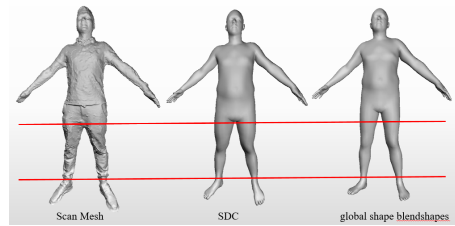

Figure 3: Comparison of fitting with SDC and original global PCA shape blendshape.

2.1 Semantic Deformation Components (SDC)

We observe some limitation of using global PCA blendshapes of the RPBM for fitting the general scanned models. The RPBMs are trained from limited number and type of body scan (e.g. SMPL is trained from CAESAR dataset containing 2,400 U.S./Canadian and 2,000 European civilians). The shape space expanded by 10 PCA basis is not sufficient to represent human bodies of various age group and various ethnicity like Asian, Hispanics and etc. More importantly, these blendshapes are defined globally, and will be unsuitable for the geometry fitting purpose. For example, shortening the leg to reduce the legs' fitting error might unexpectedly elongate the torso part. In this work, we re-parameterize the shape space with some local and semantic deformation components so that there are individual components to control the length and shape of certain body parts. We formulate the problem similar to SPLOC [Neumann et al. 2013] but with semantic measurements as sparseness and localization constraints. The advantage of fitting with SDC is shown in Fig. 3.

We evaluate our method using hundreds of scans in varies outfits, poses and occlusions. The results demonstrate that our method is highly effective and robust in rigging 3D raw human scans.

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