Bodyopt - A Character Deformation Pipeline For *Avatar: The Way of Water*

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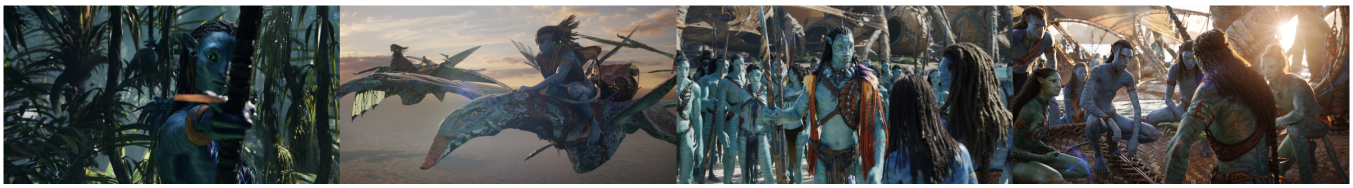

Figure 1: A selection of shots from *Avatar: The Way of Water* that utilized our character deformation pipeline. ©Disney.

ABSTRACT

We present Bodyopt, a character skin deformation framework developed for *Avatar: The Way of Water*. Our approach aims to learn the skin deformations from a given dataset and reproduce them reliably during shot production. In conjunction with the kinematic skeleton, we employ muscle fibers as an additional anatomical basis, where their length changes serve as a parametrization for the non-linear deformation components. We provide a novel way of curating the dataset to minimizing differences between similar poses, which would otherwise lead to a quality loss in the reconstruction. Our approach also handles runtime skin dynamics and utilities for artists to transfer deformations to new character types as well as extra modifiers for secondary motions like breathing. Additionally, we close the gap between final skin deformation and the representation used in Animation by providing a fast proxy solution that is based on the same input data.

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1 INTRODUCTION

Wētā FX usually employs muscle simulation to generate the final skin deformation. While this can produce great results, it is also setup intensive and requires intrinsic knowledge of anatomy, which cannot always be determined accurately for all creature types. Simulations can fail and be slow to run, thus requiring more artist time to resolv and tweak parameters to achieve the desired results. Our goal was to take the findings of Wētā FX's new facial system [Choi et al. 2022] and extend it to a full body model.

Our most important aim was to provide the production pipeline with a reliable and predictable system that could deliver the vast amount of character work required in a much shorter timeframe.

2 DATA PREPARATION

To generate the initial dataset for a character's surface, we use traditional Finite Element Method (FEM) muscle simulations. The range of motion clips consists of about 3200 frames and covers a wide range of poses.

We found that poor reconstruction results are largely connected to lack of training data or inconsistency of shapes for similar poses. To ensure a consistent reconstruction quality that is faithful to the input data, it is critical that similar poses share similar geometric features throughout the dataset.

For artists to modify the pose meshes, we provide an extensive modelling toolkit. To enable sculpting workflows across the entire training pose database, artist edits or other implicit mesh operations are stored in a non-destructive modifier stack. Some of these operations allow us to minimize their respective geometric differences across similar poses and help maintain geometric feature consistency in the dataset.

To save time when setting up a new character, we utilize our transfer system to copy already curated datasets to similar characters as a starting point.

During production, we add new poses to the dataset to improve reconstruction of scenes that were previously not well covered.

3 TRAINING AND RECONSTRUCTION

Our approach for training and reconstruction follows closely the methods outlined in Animatomy [Choi et al. 2022] with some changes to some aspects of the process.

Instead of using Linear Blend Skinning un-posing as a base layer for our linear feature component, we found that Direct Delta Mush [Le and Lewis 2019] un-posing results in a much closer initial fit and therefore better reconstruction results.

DDM forward deformation applies a rigid transform to each vertex i of the reference mesh

$$x_i = t_i + R_i d_i,$$

where d is the difference between original and smoothed vertex positions of the reference mesh, and t and R are translation and rotation components of the rigid transform respectively. If there is a change delta x associated with sculpting in the world space, the corresponding correction delta d in the unposed space can be easily recovered by solving

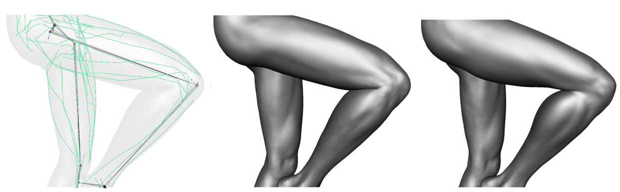
$$x_i + \delta x_i = t_i + R_i(d_i + \delta d_i).$$

To represent the non-linear part of the deformations we use strain information to encode the residual components which aren't captured by the linear reconstruction. For this feature component, we derive muscle fibers from the existing FEM muscle setup and project them onto the mesh in order to measure the difference in length over rest length. We found that having the right number of "meaningful" strains in areas with high non-linear deformations greatly improved the reconstruction results.

In order to handle localization, we rely not only on statically defined areas, but a combination of dynamic muscle influences on a given part of the surface over the period of a range of motion. This helps to inform the system which regions to generate for any given character and improves reconstruction quality. Localization is an important aspect for our deformation pipeline as it reduces the need to match poses globally and thus can exploit more variations in the training data.

4 DYNAMICS

We implement an additional dynamics layer to capture muscle jiggle due to inertia on top of the recovered quasistatic shapes. We start with tetrahedralizing the input character surface mesh in the reference configuration. On each simulation frame, given the recovered quasistatic deformed surface, we propagate the deformations to the interior of the tet mesh using simple Laplace diffusion. Note that the inverse of the Laplacian operator on the tet mesh can be precomputed to achieve better performance at run time. The tet mesh obtained through diffusion is used as a rest configuration for an FEM-based solve. We use linear elasticity since the muscles of our lean characters deviate from the quasistatic equilibrium configuration only slightly. This allows us to also precompute and reuse the elasticity stiffness matrix. However, more complex elastic models could be used as well. The bones are attached to the tet mesh via spring constraints using barycentric coordinates of the attachment points in the reference configuration.



(a) (b) (c)

Figure 2: Training components: (a) joint and strain representation, (b) base mesh before un-posing, (c) target mesh. ©Wētā FX.

5 TRANSFER

Our transfer tool is based on an implementation of [Sumner and Popović 2004] and is used in a multitude of ways throughout the system. Note that we perform transfers in the un-posed rather than world space, which helps to align the transfer results more easily with the underlying kinematic skeleton.

The second usecase for this tool is the "live transfer" workflow which allows us to transfer skin deformations from a trained character to a variety of similar looking back and midground elements. While we implemented multiple ways of dealing with different topologies and skeletal differences, the system works best if the anatomy of the target is similar to the source.

6 PRODUCTION

For *Avatar: The Way of Water* the system was used on 12 hero characters as well as 5 more generic transfer elements. The dataset for each element ended up holding between 2400 and 3600 frames to train with.

Once the initial setup and training was done, the runtime part of each element was only a fraction of the time compared to a traditional simulation. This led to a significant improvement for the skin deformation pipeline in the Creatures department for this show.

Bodyopt was used on 6691 individual elements across 2392 shots.

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