SFLSH: Shape-Dependent Soft-Flesh Avatars – Supplementary Document

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1 OVERALL SIMULATION ALGORITHM

Let the motion and deformation of an avatar model be generally described by a set of dynamic degrees of freedom (DoFs) q (to be specified throughout the document). We simulate dynamics using backward Euler numerical integration, which can be formulated as the following optimization problem [Gast et al. 2015]:

$$q = \arg\min \frac{1}{2\,h^2}\ \left(q - q^*\right)^T\ M\ \left(q - q^*\right) + V(q). \tag{1}$$

In this optimization, h is the time step, q^* the tentative state resulting from explicit integration, M is the mass matrix, and V collects all potential energy terms.

We solve the optimization using Newton's method. In the examples in the paper, and for the optimization of elasticity parameters, we limit each time step to just one Newton iteration, but the method can easily be extended for higher accuracy. In each Newton iteration, we solve the resulting linear system with a direct solver based on Cholesky factorization [Guennebaud et al. 2010].

The simulation algorithm is easily extended to include multiple bodies and/or other objects. The DoFs q are formed by concatenating the DoFs of each body, and the mass matrix M and potential energy V are built by adding the terms corresponding to each body, as well as inter-body interactions due to contact.

2 VOLUMETRIC SMPL

The simulation model is defined on top of the parametric body model SMPL [Loper et al. 2015]. SMPL is characterized by a pose θ and shape β.

Given a template body $\bar{\mathcal{X}}_0$ in reference pose, it is mapped to a person-specific body $\bar{\mathcal{X}} = f_{\text{shape}}(\bar{\mathcal{X}}_0, \beta)$ based on the shape parameters. In this unposed state, our soft-flesh avatar adds an elastic deformation to model the effects of contact or inertia. As a result of elastic deformation, a rest point $\bar{x} \in \bar{\mathcal{X}}$ transforms into a deformed point $x(\bar{x}) \in \mathcal{X}$, with $\mathcal{X}$ the deformed body. Then, the SMPL skinning transformation $\mathcal{X}_\theta = f_{\text{skinning}}(\mathcal{X}, \theta)$ based on the pose parameters defines the posed body shape $\mathcal{X}_\theta$. SMPL's skinning transformation is linear blend skinning augmented with pose and shape blend-shapes.

Even though the original SMPL is defined only for the body surface, we follow [Romero et al. 2020] to extend SMPL's blend shapes and skinning weights to the volumetric body. This is done in the following way. First, we initialize a correspondence between the surface and the skeleton, by simply finding the closest skeletal point for each surface point. Then we refine this correspondence using Laplacian smoothing. All surface quantities are extended between the surface and the skeleton by simply following the correspondence path. Note that, for the purpose of extending SMPL to the body volume, we remove the head, hands and feet.

3 SKELETAL DYNAMICS

For each body bone in the SMPL skeleton, we define a rigid transformation ϕ_i. Then, the skeleton contributes to the DoFs q the collection of rigid bone transformations $\{\phi_i\}$. We can obtain the SMPL pose θ by extracting the skeleton root transformation and the joint angles from the $\{\phi_i\}$ rigid transformations.

The skeleton contributes to the mass matrix M rigid-body inertia terms associated with each bone. Similarly, the skeleton contributes to the potential energy V: a gravity term per bone, joint constraints to maintain the skeletal structure, joint limits, and tracking constraints between the skeleton and target configurations (e.g. coming from mocap) implemented as joint rotation springs.

4 REDUCED SOFT-TISSUE DYNAMICS

To model elastic deformations, we define a skin displacement field $u(\bar{x})$ on the reference body. As mentioned earlier, we apply the skin deformation in unposed state, hence transforming the reference body shape as $x(\bar{x}) = u + \bar{x}$.

For computational efficiency, we represent the skin displacement field in a linear reduced basis, $u(\bar{x}) = U(\bar{x})\, z$, with z the vector of reduced DoFs and U the matrix of basis coefficients. We use bounded generalized biharmonic coordinates as reduced model [Wang et al. 2015], following the model architecture of Tapia et al. [2021]. In detail, the basis is computed by considering as handles a set of control points distributed throughout the body, but also the bones of the skeleton. At runtime the bones are fixed in the unposed reference state, which naturally sets Dirichlet boundary conditions

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on the surface of the bones. The control point handles are manually chosen, with a denser sampling on areas with stronger soft-tissue deformation.

Putting the bone transformations and the reduced deformation DoFs together, the total set of DoFs of our soft-body avatar is $q = (\{\phi_i\}, z)$.

We model skin elasticity without the pose transformation, as done by Romero et al. [2020], to exactly reproduce the SMPL model on static poses. This implies the definition of the deformation gradient as $F = I + \frac{\partial u}{\partial \bar{x}}$. Based on this deformation gradient, we use as strain energy density $\Psi(F)$ an orthotropic Saint Venant-Kirchhoff hyperelastic model with Fung-type saturation, also proposed by Romero et al.

The soft tissue contributes inertial and elastic terms to M and V respectively. For inertia, we integrate kinetic energy on the body volume using world-space velocities, and then differentiate with respect to the full set of DoFs q. Note that this yields inertia terms on both the reduced skin displacement DoFs z and the bone transformations (as well as cross-terms). For elasticity, we simply integrate the strain energy density Ψ on the unposed body volume.

We use an FEM discretization followed by cubature integration to approximate the integrals of inertial and elastic energy on the body volume. In our model, all body shapes use the same tetrahedral discretization, independent of the shape coefficients β, to facilitate the interpolation of elasticity parameters as a function of body shape. To compute the discretization, we create an offset surface between the body's template surface and the skeleton, at a medium skin thickness. Then, we mesh with tetrahedra the volume between the external surface and the internal offset surface. The resulting mesh is transformed to each body shape based on the shape coefficients, and we apply the spatially varying skin thickness by moving mesh nodes along the correspondence path from the external surface to the skeleton.

For cubature, we use the data-oblivious approach of Tapia et al. [2021]. Given a set of cubature samples as control points, we consider a scalar field interpolated on the volume using biharmonic weights. We want the cubature approximation to preserve the integral of the scalar field, and this is achieved by making each cubature weight equal to the integral of its corresponding biharmonic weight field.

5 CONTACT

For the examples in the paper, we formulate contact in two possible ways. First, for the interaction with rigid bodies, we sample the body surface, query for penetration with the signed distance field of the rigid body, and add to V a quadratic penetration potential for each colliding surface sample. For the interaction between bodies, we solve contact using an approximate skeletal representation. We endow the body with a hierarchy of analytical capsules that approximate the body and are transformed by each bone. When two capsules penetrate, we add again a quadratic penetration potential to V. Our contact model does not include friction.

When the body colliders with an external rigid body, contact acts directly on the soft tissue and indirectly on the skeleton, as a result of the total energy minimization. When two bodies collide, contact acts directly on the skeleton, but soft-tissue dynamics appear under fast collisions due to inertial effects.

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