

Stable Neo-Hookean Flesh Simulation

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Fig. 1. **Left:** 13 skeletal bones drive a hexahedral lattice with 45,809 elements and 156,078 degrees of freedom. **Center:** A quasistatic simulation with our new Neo-Hookean model and a Possion's ratio of $\nu = 0.488$. Wrinkles and bulges emerge from our model's excellent volume-preserving properties. An average time step with our model took 13.7 Newton iterations, 5,860 Conjugate Gradient (CG) iterations, and 25.6 seconds. **Right:** The same simulation with co-rotational elasticity and $\nu = 0.488$. The model fails to preserve volume and instead collapses the trapezius and forms a spurious fold around the shoulder blade. The artifacts persist across all values of ν . An average time step with this model took 17.9 Newton iterations, 16,183 CG iterations, and 46.6 seconds. ©Disney/Pixar

Non-linear hyperelastic energies play a key role in capturing the fleshy appearance of virtual characters. Real-world, volume-preserving biological tissues have Poisson's ratios near $1/2$, but numerical simulation within this regime is notoriously challenging. In order to robustly capture these visual characteristics, we present a novel version of Neo-Hookean elasticity. Our model maintains the fleshy appearance of the Neo-Hookean model, exhibits superior volume preservation, and is robust to extreme kinematic rotations and inversions. We obtain closed-form expressions for the eigenvalues and eigenvectors of all of the system's components, which allows us to directly project the Hessian to semi-positive-definiteness, and also leads to insights into the numerical behavior of the material. These findings also inform the design of more sophisticated hyperelastic models, which we explore by applying our analysis to Fung and Arruda-Boyce elasticity. We provide extensive comparisons against existing material models.

CCS Concepts: • Computing methodologies → Physical simulation;

Additional Key Words and Phrases: physically-based simulation, elasticity.

ACM Reference format:

Breannan Smith, Fernando de Goes, and Theodore Kim. 2017. Stable Neo-Hookean Flesh Simulation. *ACM Trans. Graph.* 1, 1, Article 1 (December 2017), 14 pages.

<https://doi.org/10.1145/nnnnnnn.nnnnnnn>

1 INTRODUCTION

The elastic energy used to model deformations determines the visual quality of a simulation, so it must be chosen carefully for virtual characters and virtual humans. The defining quality of biological

tissues such as muscle and fat is volume preservation, which is reflected in their high Poisson's ratios $\nu \in [0.45, 0.5]$ [Greaves et al. 2011], and the corresponding visual features that emerge (Fig. 2). However, this near-incompressible regime is notoriously difficult to simulate robustly and accurately. For instance, the popular co-rotational model for elasticity [Chao et al. 2010; McAdams et al. 2011; Müller et al. 2002; Nesme et al. 2009] ostensibly supports materials within this range, but it linearizes the volume term in a way that compromises both its volumetric properties and its visual results (Fig. 1, right). Alternatively, force filtering approaches [Irving et al. 2004; Teran et al. 2005] inherit the visual quality of the Neo-Hookean model, but introduce additional user parameters.

In this work, we propose a novel Neo-Hookean energy that retains the rich, volumetric character of biological materials and does not need any filter parameters. While motivated by biological tissues where $\nu \approx 0.5$, our model behaves well across a wide range of Poisson's ratios ($\nu \in [0, 0.5]$). Our model exhibits better volume preservation than equivalent filtered models, and does not break down under the large kinematic rotations that often occur in quasistatic simulations. The computational performance of our method is competitive with, and often better than, existing methods. We know of no other model that possesses all of these advantages.

We achieve these properties by performing an analysis that completely characterizes the Hessian of the energy, and results in closed-form expressions for the eigenvectors and eigenvalues of each of its terms. The eigendecomposition of the overall system can then be written as a set of compact expressions, which we use to isolate the sources of indefiniteness and project them back to semi-definiteness. As a consequence, we can safely apply our energy to Newton-type

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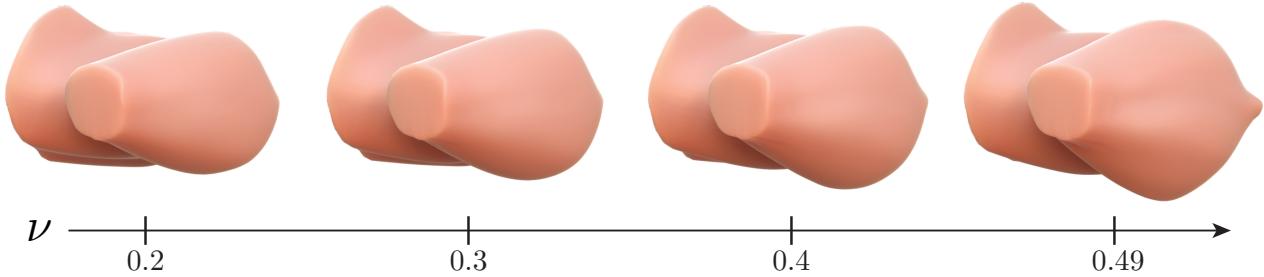


Fig. 2. Volume preservation is the key to convincing flesh simulations. We simulate an elbow flexion over a range of Poisson's ratios v with our Stable Neo-Hookean model. Smaller values of v resemble a skinning, and it is not until $v \approx 1/2$ that we obtain significant volumetric bulging in the forearm. ©Disney/Pixar

implicit integration schemes that use conjugate gradient-based linear solvers. While this analysis was motivated by our Neo-Hookean model, it is sufficiently generic that it also supports any model formulated in terms of the first and third invariants of the deformation gradient. As preliminary examples, we show how it can be extended to Fung [2013] and Arruda-Boyce [1993] elasticity. We conclude with detailed comparisons to existing hyperelastic energies. In particular, we are able to phrase the popular co-rotational model as a linearization of the Neo-Hookean energy (§5.1) and position our model on a spectrum of successive approximations to this energy.

2 BACKGROUND

Before presenting our material model, we provide a brief review of existing hyperelastic energies and numerical simulators. In the following, we represent scalars as unbolded letters (x, J), vectors as bold lowercase letters (\mathbf{x}), and matrices as bold uppercase letters (\mathbf{X}). Greek letters (Ψ, α) represent scalars.

2.1 Deformation Gradient

The fundamental measure of non-linear deformation is the deformation gradient \mathbf{F} . Here, we label its columns with vectors and its entries with scalars:

$$\mathbf{F} = \left[\begin{array}{c|c|c} \mathbf{f}_0 & \mathbf{f}_1 & \mathbf{f}_2 \end{array} \right] = \left[\begin{array}{ccc} f_0 & f_3 & f_6 \\ f_1 & f_4 & f_7 \\ f_2 & f_5 & f_8 \end{array} \right]. \quad (1)$$

Table 1 summarizes the derived quantities of \mathbf{F} we will use. One factorization requires special attention: the *rotation variant* SVD [Higham 2008; Irving et al. 2004; Twigg and Kac̆ić-Alesić 2010] of \mathbf{F} , which we write as

$$\mathbf{F} = \mathbf{U}\Sigma\mathbf{V}^T \quad \text{and} \quad \Sigma = \begin{bmatrix} \sigma_0 & 0 & 0 \\ 0 & \sigma_1 & 0 \\ 0 & 0 & \sigma_2 \end{bmatrix}. \quad (2)$$

Unlike the standard SVD convention, the rotation variant moves reflections to Σ , so \mathbf{U} and \mathbf{V} are rotations with $\det(\mathbf{U}) = \det(\mathbf{V}) = 1$, and Σ is allowed to have a negative entry.

2.2 Hyperelastic Energies

The elastic behavior of a deformable body can be specified in terms of a hyperelastic energy density Ψ , such as the co-rotational (CR)

Symbol	Definition
$\mathbf{F} = \mathbf{RS}$	Polar decomposition
$J = \det(\mathbf{F})$	Relative volume change
$\mathbf{C} = \mathbf{F}^T \mathbf{F}$	Right Cauchy-Green tensor
$I_C = \text{tr}(\mathbf{C})$	First Right Cauchy-Green invariant

Table 1. Quantities derived from the deformation gradient \mathbf{F} .

material [McAdams et al. 2011]:

$$\Psi_{\text{CR}} = \mu \|\mathbf{F} - \mathbf{R}\|_F^2 + \frac{\lambda}{2} \text{tr}^2(\mathbf{S} - \mathbf{I}). \quad (3)$$

Here, μ and λ are the Lamé constants, \mathbf{R} and \mathbf{S} form the polar decomposition of \mathbf{F} (Table 1), and \mathbf{I} is a 3×3 identity matrix. Forces can be derived from this energy by several means, but a popular approach uses the first Piola-Kirchhoff (PK1) stress tensor, which we denote $\mathbf{P}(\mathbf{F})$. The PK1 for the co-rotational material is:

$$\mathbf{P}_{\text{CR}}(\mathbf{F}) = \frac{\partial \Psi}{\partial \mathbf{F}} = \mathbf{R} \left[\mu(\mathbf{S} - \mathbf{I}) + \lambda \text{tr}(\mathbf{S} - \mathbf{I})\mathbf{I} \right]. \quad (4)$$

After integrating over a volume V and changing variables to vertex displacements \mathbf{u} , we obtain a matrix, $\mathbf{VP}(\mathbf{F}) \frac{\partial \mathbf{F}}{\partial \mathbf{u}}$, whose columns are vertex forces. The term $\frac{\partial \mathbf{F}}{\partial \mathbf{u}}$ varies based on the element type, e.g. tetrahedra or hexahedra, and basis type, e.g. linear or quadratic [Bargteil and Cohen 2014]. Other texts describe this derivation [Müller et al. 2008; Sifakis and Barbic 2012], so we will deal directly with Ψ and $\mathbf{P}(\mathbf{F})$ and defer to these references for further details.

2.3 Robustness Challenges

A key drawback of non-linear hyperelastic energies is that they usually contain singularities. Early work on deformable simulation [Hirota et al. 2001] detected these “illegal” states and carefully avoided them using a backtracking line search. These searches are challenging to perform robustly, because a NaN in a single degree of freedom can quickly grow to pollute larger regions of the simulation. This backtracking approach also precludes simulations where the solution contains inverted elements, which often occurs in production environments.

Irving et al. [2004] described an explicit method for simulating non-linear materials that instead used the rotation variant SVD (Eqn. 2) to write a *filtered* stress tensor $\mathbf{P}(\Sigma)$ defined in \mathbf{F} 's principal stretch space Σ . For specific values of Σ where $\mathbf{P}(\Sigma)$ was known to behave badly, the tensor was clamped to constant or linear functions. Thus, no backtracking was needed to avoid illegal states. In order to use this method, the user identifies badly behaved regions of $\mathbf{P}(\Sigma)$ and sets a filtering threshold. Notably, the usual convention for the rotation variant SVD is to push reflections into the smallest singular value, but subsequent work has shown that this can introduce subtle problems, including discontinuities and non-optimal inversion recovery directions [Georgii and Westermann 2008; Schmedding and Teschner 2008]. The work of Civit-Flores and Susin [2014] provides an excellent overview.

Implicit integration of the force filtering approach was described by Teran et al. [2005]. Since the 4thorder tensor $\frac{\partial \mathbf{P}(\mathbf{F})}{\partial \mathbf{F}}$ may become indefinite, a separate derivation was needed to guarantee its positive definiteness. The tensor was diagonalized into one 3×3 and three 2×2 matrices, and eigenvalues were clamped to a threshold. This approach has the limitation that Ψ , $\mathbf{P}(\mathbf{F})$ and $\frac{\partial \mathbf{P}(\mathbf{F})}{\partial \mathbf{F}}$ can drift out of sync. This issue was alleviated by Stomakhin et al. [2012] by applying the filter directly to Ψ . Xu et al. [2015] proposed an alternative where users design force curves in principal stretch space. We instead present an energy that is agnostic to any reflection convention, even in the presence of inverted elements.

Alternative deformation schemes such as position-based dynamics [Bender et al. 2015; Umetani et al. 2014] and projective dynamics [Bouaziz et al. 2014] have recently emerged. One advantage of these schemes is that the Hessian $\frac{\partial^2 \Psi}{\partial \mathbf{F}^2}$ does not need to be constructed explicitly. However, projective dynamics still needs to specify filtering thresholds and reflection conventions [Narain et al. 2016; Wang and Yang 2016] to avoid numerical singularities. The advantage that our model requires neither carries over directly.

3 ENERGY FORMULATION

Following the preceding discussion, we design a new hyperelastic energy that is stable in four important ways:

- **Inversion stability:** The energy is singularity-free, and does not need any filters or thresholds.
- **Reflection stability:** The energy is well-behaved regardless of the reflection convention used in the SVD.
- **Rest stability:** Under zero load, an element's rest shape is preserved.
- **Meta-stability under degeneracy:** Under point, line, and plane degeneracies, the forces are defined up to rotation.

We start by examining existing hyperelastic energies that go by the name “Neo-Hookean.”

3.1 Existing Neo-Hookean Energies

The most common version of Neo-Hookean elasticity is (see, e.g., [Bonet and Wood 2008]):

$$\Psi_{\text{Neo}} = \frac{\mu}{2}(I_C - 3) - \mu \log J + \frac{\lambda}{2}(\log J)^2. \quad (5)$$

Here, I_C and J are defined in Table 1. However, many other versions appear in the literature:

$$\Psi_A = \frac{\mu}{2}(I_C - 3) - \mu \log J + \frac{\lambda}{2}(J - 1)^2 \quad [\text{Ogden 1997}]$$

$$\Psi_B = \frac{\mu}{2}(J^{-2/3}I_C - 3) + \frac{\lambda}{2}(J - 1)^2 \quad [\text{Bower 2009}]$$

$$\Psi_C = \frac{\mu}{2}(J^{-2/3}I_C - 3) + \frac{\lambda}{2}(J - 1) \quad [\text{Wang and Yang 2016}]$$

We examine these energies under the Valanis-Landel hypothesis [Xu et al. 2015], which posits that many hyperelastic energies can be separated into length (1D), area (2D), and volume (3D) components. The above models contain length and volume terms, but no area terms. Adding an area term yields a Mooney-Rivlin model.

1D Length Term: Mooney [1940] originally proposed the energy

$$\Psi_M = \frac{\mu}{2}(I_C - 3), \quad (6)$$

which was later dubbed the “Neo-Hookean” energy by Rivlin [1948]. When unconstrained, this energy achieves its minimum when the element has collapsed to zero volume, i.e. when $I_C = 0$ and $\Psi_M = -3$. Mooney additionally imposed the hard constraint that $J = 1$, so the energy is instead minimized at the volume-preserving configuration that is the closest to the stretch space origin. Even without this constraint, we note that Ψ_M is *well-behaved under inversion*. The energy relative to a zero-volume configuration is always well-defined irrespective of an element’s current state.

In contrast, the Ψ_B and Ψ_C energies use a modified Neo-Hookean term $\mu/2(J^{-2/3}I_C - 3)$ [Rivlin 1948]. The $J^{-2/3}$ term factors off the nearest squared isotropic stretch from I_C , leaving only the squared distortional part of the deformation. It also introduces numerical problems by growing without bound under compression, i.e. as $J \rightarrow 0$, and becoming undefined at $J = 0$. Therefore, we prefer to use a Ψ_M length term in lieu of a modified energy.

3D Volume Term: The remaining terms in the above energies are volume-preserving penalty terms. The volume terms from Ψ_{Neo} clearly present numerical difficulties:

$$\Psi_{\text{Neo},\text{volume}} = -\mu \log J + \frac{\lambda}{2}(\log J)^2. \quad (7)$$

In addition to growing unbounded as $J \rightarrow 0$, they become infeasible for $J < 0$. These difficulties motivated the design of the force filtering approach [Irving et al. 2004]. Any energy with a logarithm, including $\Psi_{\text{A},\text{volume}} = -\mu \log J + \lambda/2(J - 1)^2$, will also have these problems.

In contrast, $\Psi_{\text{B},\text{volume}} = \lambda/2(J - 1)^2$ does not have these issues, and is bounded, well-defined, and invertible. Such terms have been used [Martin et al. 2011; Teschner et al. 2004] to sidestep the need for any inversion handling. A promising candidate is then

$$\Psi_D = \frac{\mu}{2}(I_C - 3) + \frac{\lambda}{2}(J - 1)^2, \quad (8)$$

but it has a key drawback that we must address.

3.2 Rest Stabilization

While Ψ_D possesses inversion stability, it lacks what we will call *rest stability*. In the solid mechanics literature (e.g. [Bonet and Wood 2008], §6.4.3) it is often mentioned that the hyperelastic energy

should vanish at identity. This occurs with Ψ_D , but it is more important that the PK1 resolve to zero, as this is the true indicator that the energy has been extremized. Otherwise, forces appear when the body is at rest and overwrite the intended rest state with a different, parameter-dependent state. This is a known side effect of certain barrier functions [Schüller et al. 2013]. One solution is to increase the volume penalty constant λ dramatically in order to reduce the visual appearance of the artifact (e.g. [Blemker et al. 2005] suggests $\sim 1000\mu$). We avoid this approach, because it precludes the artifact-free simulation of materials with lower Poisson's ratios. Scaling λ also increases the indefiniteness of the Hessian (see §4.6), and should be done judiciously.

Intuitively, the problem is that the effective rest state no longer coincides with $J = 1$. Instead, it coincides with a smaller J that causes an element to slightly deflate. Consequently, we ask whether we can *inflate* each element so that, when it deflates, it settles to rest at $J = 1$. To answer this question, we consider the PK1 of Ψ_D :

$$\mathbf{P}_D(\mathbf{F}) = \mu\mathbf{F} + \lambda \frac{\partial J}{\partial \mathbf{F}}(J - 1). \quad (9)$$

An energy is rest stable if $\mathbf{P}_D(\mathbf{I}) = 0$, but $\mathbf{P}_D(\mathbf{I})$ is nonzero:

$$\mathbf{P}_D(\mathbf{I}) = \mu\mathbf{I} + \lambda \frac{\partial \det(\mathbf{I})}{\partial \mathbf{F}}(\det(\mathbf{I}) - 1) = \mu\mathbf{I}. \quad (10)$$

To recover rest stability, we modify $(J - 1)^2$ to shift the root from 1 to α , i.e. we inflate the element to a volume greater than one:

$$\begin{cases} \Psi_E &= \frac{\mu}{2}(I_C - 3) + \frac{\lambda}{2}(J - \alpha)^2 \\ \mathbf{P}_E(\mathbf{F}) &= \mu\mathbf{F} + \lambda \frac{\partial J}{\partial \mathbf{F}}(J - \alpha). \end{cases}$$

Solving for an α that satisfies $\mathbf{P}_E(\mathbf{I}) = 0$ yields $\alpha = 1 + \mu/\lambda$:

$$\Psi_E = \frac{\mu}{2}(I_C - 3) + \frac{\lambda}{2} \left(J - 1 - \frac{\mu}{\lambda} \right)^2. \quad (11)$$

We can additionally expand the quadratic to obtain:

$$\Psi_E = \frac{\mu}{2}(I_C - 3) - \mu(J - 1) + \frac{\lambda}{2}(J - 1)^2 + \left(\frac{\mu}{\lambda} \right)^2. \quad (12)$$

Since constants disappear under differentiation, this material model is functionally equivalent to:

$$\Psi_E = \frac{\mu}{2}(I_C - 3) - \mu(J - 1) + \frac{\lambda}{2}(J - 1)^2. \quad (13)$$

This is strikingly similar to the original Ψ_{Neo} from Eqn. 5, except the $\log J$ terms have been replaced with $(J - 1)$. We make two important observations. First, Ψ_{Neo} is rest-stable, but not singularity-free. Second, $(J - 1)$ is the first term in the Taylor series of $\log J$ at $J = 1$. Essentially, we have performed a singularity-removing Taylor truncation of Ψ_{Neo} about a volume preserving state, resulting in an inversion and rest stable material model. We can also verify that our energy Ψ_E is reflection stable. The I_C term involves the squared singular values of \mathbf{F} , so any negation convention is irrelevant. Since the J term is the product of the singular values, the sign convention is again irrelevant. Similar reasoning can be used for PK1, and we show in §4.5.1 that the Hessian is agnostic to the convention as well.

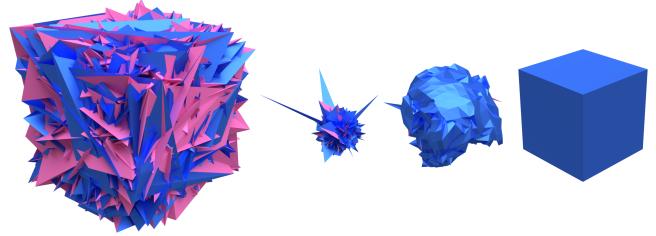


Fig. 3. To stress test our stable Neo-Hookean ($\nu = 0.49$) model, we randomly scramble a cube's vertices within a space of twice its volume. The cube recovers its rest pose, highlighting our model's robustness under extreme, inverted configurations.

3.3 Meta-Stability Under Degeneracy

The energy now has inversion, reflection, and rest stability. However, its behavior must be examined under degeneracy, i.e. when an element has been crushed to a plane, line, or point. This examination can also be viewed as a Drucker stability analysis [Bower 2009].

An extensive treatment of all three degeneracies is given in the supplemental materials, but we will sketch the main results here. For the case where an element is crushed to a plane, the energy is stable. Material forces appear along the normal direction to the plane, and work to restore the original shape.

When the element is crushed to a line, the energy is meta-stable. The forces resolve to zero, but the Hessian is negative definite. For a material that is invertible, this meta-stable state is correct. If an unconstrained element has been crushed to exactly a line, the shape it should return to is underdetermined, because the configuration is equidistant from all possible rotations of the original shape about the line. However, negative definiteness guarantees that any perturbation (e.g. momentum) will select a rotation, and the element will self-restore. The alternative to meta-stability is a singularity at this configuration, which is clearly undesirable.

When an element is crushed to a point, i.e. $\mathbf{F} = 0$, the forces disappear and the Hessian is positive definite, which mean the configuration will remain stable even in the presence of perturbations. This behavior is undesirable, though the basin of attraction is vanishingly small for Poisson's ratios that correspond to biological tissue ($\nu \geq 0.45$). For completeness, we introduce one more term to eliminate the basin across a wide range of ν .

We add a *regularized origin barrier* $\log(I_C + \delta)$ that inserts a peak of negative-definiteness about $\mathbf{F} = 0$, but uses δ to smooth away the logarithmic singularity. In the supplemental material, we show that $\delta = 1$ is the value that exactly produces semi-definiteness at $\mathbf{F} = 0$. Our final energy is then:

$$\Psi_{\text{new}} = \frac{\mu}{2}(I_C - 3) + \frac{\lambda}{2}(J - \alpha)^2 - \frac{\mu}{2} \log(I_C + 1). \quad (14)$$

As we derive in the supplemental material, the rest-stability term now shifts to $\alpha = 1 + \mu/\lambda - (\mu/4)\lambda$.

3.4 Lamé Reparameterization

With this energy, we now consider the reparameterization of the material parameters μ and λ in order to maintain consistency with Hooke's law. To this end, we shift the values of μ and λ so that our model reproduces the PK1 of linear elasticity, which is of the form

$$\mathbf{P}(\mathbf{F}) = 2\mu_{\text{Lamé}}\epsilon + \lambda_{\text{Lamé}} \text{tr}(\epsilon)\mathbf{I}, \quad (15)$$

where $\epsilon = 1/2(\mathbf{F} + \mathbf{F}^T) - \mathbf{I}$ is the linearized strain tensor, and the coefficients $\mu_{\text{Lamé}}$ and $\lambda_{\text{Lamé}}$ are the Lamé parameters in linear elasticity. The linearization of the stress derived from Eqn. 14 becomes consistent with this expression if we set $\mu = 4/3\mu_{\text{Lamé}}$ and $\lambda = \lambda_{\text{Lamé}} + 5/6\mu_{\text{Lamé}}$. The expression for Poisson's ratio shifts to:

$$\nu = \frac{\lambda - (5/8)\mu}{2(\lambda + (1/8)\mu)}. \quad (16)$$

Note that the same methodology can be applied to any of the previous energies. In particular, the reparameterization of Eqn. 13 yields $\mu = \mu_{\text{Lamé}}$, $\lambda = \lambda_{\text{Lamé}} + \mu_{\text{Lamé}}$, and $\nu = (\lambda - \mu)/(2\lambda)$.

Using this new expression for Poisson's ratio (Eqn. 16), we can analyze our energy to confirm that it does not introduce any spurious minima over the range $\nu \in [0, 0.5]$. The details are again given in the supplemental materials, and we will sketch the results here. We are able to show symbolically that the critical points of Ψ_{new} (including maxima and saddle points) only appear under uniform scaling. Using techniques similar to that employed for meta-stability, we analyze this deformation mode and find that spurious minima only appear when $\lambda/\mu < 0.1525$. This corresponds to the auxetic regime of $\nu \leq -0.85$, so our model is stable for any $\nu \in [0, 0.5]$.

4 ENERGY EIGENANALYSIS

We show that it is possible to perform a complete eigenanalysis of Eqn. 14. In particular, we construct closed-form eigenvalues and eigenvectors of each of the terms in the Hessian, and obtain a compact expression for the eigendecomposition of their sum. These expressions will be used to construct positive semi-definite versions of the Hessian, and also to develop a qualitative understanding of the energy. We begin by specifying a notation for 4th order tensors.

4.1 Tensor Notation

There are many n^{th} order tensor notations (e.g. [Kolda and Bader 2009; Simmonds 2012]), but we will specialize to 4th order tensors. Similar to Golub and Van Loan [2012], we define vectorization $\text{vec}(\cdot)$ as column-wise flattening of a matrix into a vector:

$$\mathbf{A} = \begin{bmatrix} a & c \\ b & d \end{bmatrix} \quad \text{vec}(\mathbf{A}) = \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix}. \quad (17)$$

Since $\text{vec}(\mathbf{A})$ is a vector, we could denote it as \mathbf{a} . However, we will add the symbol $\check{\cdot}$ to indicate that it is a vectorized matrix, i.e. $\text{vec}(\mathbf{A}) = \check{\mathbf{a}}$. We denote 4th order tensors in matrix-of-matrices

form using blackboard bold:

$$\mathbb{A} = \begin{bmatrix} \begin{bmatrix} a & c \\ b & d \end{bmatrix} & \begin{bmatrix} i & k \\ j & l \end{bmatrix} \\ \begin{bmatrix} e & g \\ f & h \end{bmatrix} & \begin{bmatrix} m & o \\ n & p \end{bmatrix} \end{bmatrix} = \begin{bmatrix} [\mathbf{A}_{00}] & [\mathbf{A}_{01}] \\ [\mathbf{A}_{10}] & [\mathbf{A}_{11}] \end{bmatrix}.$$

When $\text{vec}(\cdot)$ is applied, two unfoldings reorder the 4th order tensor into a 2nd order matrix:

$$\begin{aligned} \text{vec}(\mathbb{A}) &= \left[\begin{array}{c|c|c|c} \text{vec}(\mathbf{A}_{00}) & \text{vec}(\mathbf{A}_{10}) & \text{vec}(\mathbf{A}_{01}) & \text{vec}(\mathbf{A}_{11}) \end{array} \right] \\ &= \begin{bmatrix} a & e & i & m \\ b & f & j & n \\ c & g & k & o \\ d & h & l & p \end{bmatrix} = \check{\mathbf{A}}. \end{aligned}$$

To emphasize that a matrix is a vectorized ("flattened") tensor, we again use the $\check{\cdot}$ notation, as shown in the $\check{\mathbf{A}}$ above. This vectorization convention differs from Teran et al. [2005], which clusters the diagonal entries of the submatrices in \mathbb{A} . Our convention will allow us to write several expressions in terms of cross products.

4.2 First Piola-Kirchhoff Stress (PK1)

We start from the PK1 for Eqn. 14,

$$\mathbf{P}(\mathbf{F}) = \mu \left(1 - \frac{1}{I_C + 1} \right) \mathbf{F} + \lambda(J - \alpha) \frac{\partial J}{\partial \mathbf{F}}, \quad (18)$$

where $\alpha = 1 + \mu/\lambda - (\mu/4)\lambda$. We omit the subscript, as we only consider one model in this section. Using the column-wise notation for \mathbf{F} (Eqn. 1) and the identity $J = \mathbf{f}_0 \cdot (\mathbf{f}_1 \times \mathbf{f}_2)$, we write $\frac{\partial J}{\partial \mathbf{F}}$ (a.k.a. the cofactor matrix) as cross products:

$$\frac{\partial J}{\partial \mathbf{F}} = \left[\begin{array}{c|c|c} \mathbf{f}_1 \times \mathbf{f}_2 & \mathbf{f}_2 \times \mathbf{f}_0 & \mathbf{f}_0 \times \mathbf{f}_1 \end{array} \right]. \quad (19)$$

This is a convenient shorthand for computing $\frac{\partial J}{\partial \mathbf{F}}$, and will be useful when analyzing $\frac{\partial^2 J}{\partial \mathbf{F}^2}$.

4.3 The Energy Hessian Terms

Using the scalar notation for \mathbf{F} (see Eqn. 1), we can write the Hessian of the energy in 4th-order matrix-of-matrices form

$$\frac{\partial^2 \Psi}{\partial \mathbf{F}^2} = \frac{\partial \mathbf{P}(\mathbf{F})}{\partial \mathbf{F}} = \begin{bmatrix} \begin{bmatrix} \frac{\partial \mathbf{P}(\mathbf{F})}{\partial \mathbf{f}_0} \end{bmatrix} & \begin{bmatrix} \frac{\partial \mathbf{P}(\mathbf{F})}{\partial \mathbf{f}_3} \end{bmatrix} & \begin{bmatrix} \frac{\partial \mathbf{P}(\mathbf{F})}{\partial \mathbf{f}_6} \end{bmatrix} \\ \begin{bmatrix} \frac{\partial \mathbf{P}(\mathbf{F})}{\partial \mathbf{f}_1} \end{bmatrix} & \begin{bmatrix} \frac{\partial \mathbf{P}(\mathbf{F})}{\partial \mathbf{f}_4} \end{bmatrix} & \begin{bmatrix} \frac{\partial \mathbf{P}(\mathbf{F})}{\partial \mathbf{f}_7} \end{bmatrix} \\ \begin{bmatrix} \frac{\partial \mathbf{P}(\mathbf{F})}{\partial \mathbf{f}_2} \end{bmatrix} & \begin{bmatrix} \frac{\partial \mathbf{P}(\mathbf{F})}{\partial \mathbf{f}_5} \end{bmatrix} & \begin{bmatrix} \frac{\partial \mathbf{P}(\mathbf{F})}{\partial \mathbf{f}_8} \end{bmatrix} \end{bmatrix}, \quad (20)$$

where each entry is defined as

$$\begin{aligned} \frac{\partial P(\mathbf{F})}{\partial f_i} = & \underbrace{\mu \left(1 - \frac{1}{I_C + 1}\right) \frac{\partial \mathbf{F}}{\partial f_i}}_{T_i} + \underbrace{\mu \frac{2}{(I_C + 1)^2} \mathbf{F} f_i}_{M_i} \\ & + \lambda \underbrace{\frac{\partial J}{\partial \mathbf{F}} \frac{\partial J}{\partial f_i}}_{G_i} + \underbrace{\lambda(J - \alpha) \frac{\partial^2 J}{\partial \mathbf{F} \partial f_i}}, \end{aligned} \quad (21)$$

and each $\frac{\partial P(\mathbf{F})}{\partial f_i} \in \mathbb{R}^{3 \times 3}$. Since we will examine each of the terms in detail, we have tagged them as T_i , M_i , G_i and H_i , respectively the Tikhonov, Mu, volume Gradient and volume Hessian terms. The complete Hessian is then their sum

$$\begin{aligned} \frac{\partial^2 \Psi}{\partial \mathbf{F}^2} = & \mu \left(1 - \frac{1}{I_C + 1}\right) \mathbb{T} + \mu \frac{2}{(I_C + 1)^2} \mathbb{M}(\mathbf{F}) \\ & + \lambda \mathbb{G}(\mathbf{F}) + \lambda(J - \alpha) \mathbb{H}(\mathbf{F}). \end{aligned} \quad (22)$$

We will examine the eigensystem of each term, and then build the system that results from their sum.

4.4 The Tikhonov, Mu, and Gradient Terms

We start with the Tikhonov term. Since $\frac{\partial \mathbf{F}}{\partial f_i}$ is zero except in the i th entry, this becomes an identity matrix under vectorization:

$$\text{vec}(\mathbb{T}) = \check{\mathbf{T}} = \mathbf{I}, \quad (23)$$

where \mathbf{I} denotes a 9×9 identity matrix. This matrix is full-rank, positive definite, independent of the values in \mathbf{F} , and serves as a diagonal (Tikhonov) regularizer for the rest of the energy.

For the Mu term, we vectorize \mathbf{F} into a 9-vector, $\text{vec}(\mathbf{F}) = \check{\mathbf{f}}$, which allows the tensor to be written as an outer product:

$$\text{vec}(\mathbb{M}) = \check{\mathbf{M}} = \check{\mathbf{f}} \check{\mathbf{f}}^T. \quad (24)$$

This rank-one matrix has a single non-zero eigenvalue,

$$\|\check{\mathbf{f}}\|_2^2 \equiv \|\mathbf{F}\|_F^2 \equiv (\sigma_0^2 + \sigma_1^2 + \sigma_2^2), \quad (25)$$

where $\|\cdot\|_F$ denotes the Frobenius norm and $\{\sigma_i\}$ are the singular values from Eqn. 2. The eigenvector is $\check{\mathbf{f}}$ up to normalization: $\check{\mathbf{f}} / \|\check{\mathbf{f}}\|$. The eigenvalue is always non-negative, and if \mathbf{F} contains a large stretch, the eigenvalue will be large as well.

The Gradient term has a similar structure. Using the vectorization $\text{vec}(\frac{\partial J}{\partial \mathbf{F}}) = \check{\mathbf{g}}$, the tensor becomes an outer product:

$$\text{vec}(\mathbb{G}) = \check{\mathbf{G}} = \check{\mathbf{g}} \check{\mathbf{g}}^T. \quad (26)$$

Again, there is a single non-zero, non-negative, eigenvalue:

$$\|\check{\mathbf{g}}\|_2^2 \equiv \left\| \frac{\partial J}{\partial \mathbf{F}} \right\|_F^2 \equiv [(\sigma_0 \sigma_1)^2 + (\sigma_0 \sigma_2)^2 + (\sigma_1 \sigma_2)^2]. \quad (27)$$

The eigenvector is $\check{\mathbf{g}}$ up to normalization: $\check{\mathbf{g}} / \|\check{\mathbf{g}}\|$.

4.5 The Volume Hessian

The H_i term is more involved. Vectorizing H_i reveals the structure,

$$\text{vec}(\mathbb{H}) = \check{\mathbf{H}} = \begin{bmatrix} 0 & -\hat{\mathbf{f}}_2 & \hat{\mathbf{f}}_1 \\ \hat{\mathbf{f}}_2 & 0 & -\hat{\mathbf{f}}_0 \\ -\hat{\mathbf{f}}_1 & \hat{\mathbf{f}}_0 & 0 \end{bmatrix}, \quad (28)$$

where the symbol $\widehat{\cdot}$ denotes a cross-product matrix:

$$\widehat{\mathbf{x}} = \begin{bmatrix} 0 & -x_2 & x_1 \\ x_2 & 0 & -x_0 \\ -x_1 & x_0 & 0 \end{bmatrix}. \quad (29)$$

The $\check{\mathbf{H}}$ matrix forms a *self-similar* cross product matrix. Eqn. 28 contains cross-product matrices, and its blocks form a macro-structure that is a cross-product matrix. Similar cross-product-like structures will continue to appear later.

4.5.1 Volume Hessian Eigenvalues. The eigenvalues of $\check{\mathbf{H}}$ can be factored into two characteristic polynomials:

$$\varepsilon^3 - \text{tr}(\mathbf{C})\varepsilon - 2J = 0 \quad (30)$$

$$\varepsilon^3 - \text{tr}(\mathbf{C})\varepsilon^2 + \frac{1}{2}(\text{tr}^2(\mathbf{C}) - \text{tr}(\mathbf{C}^2))\varepsilon - \det(\mathbf{C}) = 0, \quad (31)$$

where \mathbf{C} is from Table 1, and ε denotes the eigenvalues of $\check{\mathbf{H}}$. The usual λ notation for eigenvalues has been put aside and replaced by ε because λ is already reserved as a material constant.

Eqn. 31 is simpler to solve, as it corresponds to the characteristic polynomial of \mathbf{C} . Given its roots $(\varepsilon_\alpha, \varepsilon_\beta, \varepsilon_\gamma)$, six of the eigenvalues of $\check{\mathbf{H}}$ are $(\pm\sqrt{\varepsilon_\alpha}, \pm\sqrt{\varepsilon_\beta}, \pm\sqrt{\varepsilon_\gamma})$. The square roots of eigenvalues can be restated using the singular values of \mathbf{F} :

$$\begin{aligned} \varepsilon_3 &= \sigma_0 & \varepsilon_6 &= -\sigma_0 \\ \varepsilon_4 &= \sigma_1 & \varepsilon_7 &= -\sigma_1 \\ \varepsilon_5 &= \sigma_2 & \varepsilon_8 &= -\sigma_2. \end{aligned} \quad (32)$$

If the SVD of \mathbf{F} has been computed, then six of the eigenvalues of $\check{\mathbf{H}}$ are already known.

For the remaining three eigenvalues, Eqn. 30 is a depressed cubic whose roots can be obtained directly:

$$\varepsilon_k = 2\sqrt{\frac{I_C}{3}} \cos \left[\frac{1}{3} \left(\arccos \left(\frac{3J}{I_C} \sqrt{\frac{3}{I_C}} \right) + 2\pi k \right) \right] \quad k = 0, 1, 2. \quad (33)$$

We now have all of the eigenvalues of $\check{\mathbf{H}}$. The negations in Eqn. 32 and the I_C and J terms in Eqn. 33 render the reflection convention applied to the singular values irrelevant.

There are *always* negative eigenvalues in the volume Hessian. Three of the six values $\varepsilon_{3\dots 8}$ are less than or equal to zero, and the cosine function in $\varepsilon_{0\dots 2}$ guarantees that another one or two eigenvalues are negative. Moreover, we have determined that the other eigenvalues in $\frac{\partial^2 \Psi}{\partial \mathbf{F}^2}$ are non-negative, so the volume Hessian is the *only* possible source of negative eigenvalues.

We investigate further by examining the geometry of $J = \det(\mathbf{F})$ in principal stretch space [Ogden 1997; Stomakhin et al. 2012; Xu et al. 2015]. The 2D case is easier to visualize, and the intuition carries over to 3D. As shown in red (Fig. 4(a)), the set of volume-preserving configurations form two distinct, disconnected sets. This reflects the non-convexity of $J = \det(\mathbf{F})$ [Liu et al. 2016], and its saddle-point structure is visible in the contours. The red curve closely resembles the “primary contour” of Stomakhin et al. [2012].

The red points are energetically equivalent, so points outside this curve have no preferred Newton direction, even when the energy is squared, e.g. $(J - 1)^2$. Additional regularization is needed to resolve this ambiguity, which is the role played by the other terms in $\frac{\partial^2 \Psi}{\partial \mathbf{F}^2}$.

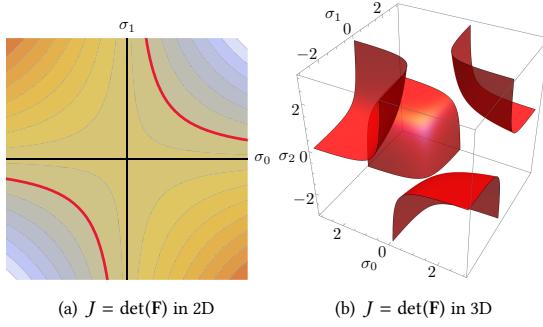


Fig. 4. The set of volume-preserving configurations in 2D and 3D stretch space are shown in red. The energy's saddle-point structure is visible in 2D.

The situation worsens in 3D, as the set of volume-preserving configurations forms four components (Fig. 4(b)). The intuition remains that saddle points exist everywhere and need to be regularized.

The structure we see in Eqns. 32 and 33 extends the understanding of the findings in Teran et al. [2005]. There, they factor the Hessian into one 3×3 and three 2×2 eigensystems. This corresponds exactly to the three entangled roots we found for Eqn. 33 and the three pairwise roots we found for Eqn. 32. This underscores the fact that our current analysis can be applied to any system that uses $J = \det(\mathbf{F})$, and is not specific to the energy $\Psi_{\text{volume}} = (J - 1)^2$.

4.5.2 Volume Hessian Eigenvectors. The eigenvectors of $\check{\mathbf{H}}$ can be written in terms of $\check{\mathbf{Q}}$ from the eigendecomposition $\check{\mathbf{H}} = \check{\mathbf{Q}}\Lambda\check{\mathbf{Q}}^T$. However, we prefer the tensor form:

$$\mathbf{Q} = \begin{bmatrix} [\mathbf{Q}_0] & [\mathbf{Q}_3] & [\mathbf{Q}_6] \\ [\mathbf{Q}_1] & [\mathbf{Q}_4] & [\mathbf{Q}_7] \\ [\mathbf{Q}_2] & [\mathbf{Q}_5] & [\mathbf{Q}_8] \end{bmatrix}. \quad (34)$$

Each eigenvector is then a 3×3 matrix instead of a 9-vector.

We start with the eigenvectors corresponding to Eqn. 31. The eigenvector corresponding to ε_3 yields an elegant structure,

$$\mathbf{Q}_3 = \frac{1}{\sqrt{2}} \mathbf{U} \mathbf{D}_3 \mathbf{V}^T \quad (35)$$

$$\mathbf{D}_3 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & -1 & 0 \end{bmatrix}, \quad (36)$$

where \mathbf{U} and \mathbf{V} are from the SVD of \mathbf{F} (Eqn. 2) and the $1/\sqrt{2}$ is a normalization factor. This eigenvector has a “pseudo-cross-product” structure that we have not seen anywhere else. The middle matrix \mathbf{D}_3 is a cross product matrix for the basis vector $\mathbf{e}_0 = [-1 \ 0]^T$. In fact, for the special case where $\mathbf{U}=\mathbf{V}$, Eqn. 35 becomes a standard cross product on the first column of \mathbf{U} , i.e. $\mathbf{Q}_3 = 1/\sqrt{2} \hat{\mathbf{u}}_0$. Eqn. 35 has a more general form where \mathbf{U} and \mathbf{V} differ, and corresponds to an infinitesimal rotation along the σ_0 axis in stretch space.

The complementary eigenvector for ε_6 , has a similar structure:

$$\mathbf{Q}_6 = \frac{1}{\sqrt{2}} \mathbf{U} \mathbf{D}_6 \mathbf{V}^T \quad (37)$$

$$\mathbf{D}_6 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}. \quad (38)$$

Note the negative has been removed from the last row. \mathbf{D}_3 has been multiplied by a reflection, making \mathbf{Q}_6 a reflected pseudo-cross-product. This corresponds to an infinitesimal rotation along the antipodal axis to \mathbf{D}_3 . The eigenvectors for $\mathbf{Q}_4, \mathbf{Q}_5, \mathbf{Q}_7$ and \mathbf{Q}_8 follow analogously as the cross products for $\mathbf{e}_1 = [0 \ -1 \ 0]^T$ and $\mathbf{e}_2 = [0 \ 0 \ -1]^T$. We explicitly list all six eigenvectors in Appendix A.

The eigenvectors for the depressed cubic (Eqn. 30) are also defined by \mathbf{U} and \mathbf{V} , but contain a conventional diagonal,

$$\mathbf{Q}_k = \frac{1}{q_k} \mathbf{U} \mathbf{D}_k \mathbf{V}^T \quad k = 0 \dots 2 \quad (39)$$

$$\mathbf{D}_k = \begin{bmatrix} \sigma_0 \sigma_2 + \sigma_1 \varepsilon_k & 0 & 0 \\ 0 & \sigma_1 \sigma_2 + \sigma_0 \varepsilon_k & 0 \\ 0 & 0 & \varepsilon_k^2 - \sigma_2^2 \end{bmatrix}, \quad (40)$$

where $q_k = \|\mathbf{D}_k\|_F$ is a normalization factor. A Mathematica notebook `Verify_Eigenvectors.nb` that symbolically confirms this eigensystem is included in the supplemental materials.

4.6 The Complete Eigensystem

With these closed-form expressions for the individual terms, we can analyze the complete system, which we denote $\check{\mathbf{A}}$ for Assembled. The vectorized version of Eqn. 22 is:

$$\check{\mathbf{A}} = \mu \left(1 - \frac{1}{I_C + 1} \right) \mathbf{I} + \mu \frac{2}{(I_C + 1)^2} \check{\mathbf{f}} \check{\mathbf{f}}^T + \lambda \check{\mathbf{g}} \check{\mathbf{g}}^T + \lambda (J - \alpha) \check{\mathbf{H}}. \quad (41)$$

Deriving expressions for the eigenvalues of a sum of matrices is generally non-trivial [Knutson and Tao 2001]. However, our energy has a special structure that allows us to obtain simple expressions for this system.

Since the $\mu(1 - \frac{1}{I_C + 1})\mathbf{I}$ term is diagonal, it has nine identical eigenvalues that can be directly added to the eigenvalues of any existing system. The main difficulty arises from computing the sum $\mu \frac{2}{(I_C + 1)^2} \check{\mathbf{f}} \check{\mathbf{f}}^T + \lambda \check{\mathbf{g}} \check{\mathbf{g}}^T + \lambda (J - \alpha) \check{\mathbf{H}}$. However, both $\check{\mathbf{f}} \check{\mathbf{f}}^T$ and $\check{\mathbf{g}} \check{\mathbf{g}}^T$ are rank-one matrices, which allows the problem to be viewed as a *rank-two update* to the eigensystem for $\lambda(J - \alpha) \check{\mathbf{H}}$.

The problem can be simplified using deflation [Bunch et al. 1978]. To this end, we show in Appendix B that both $\check{\mathbf{g}}$ and $\check{\mathbf{f}}$ are orthogonal to the six pseudo-cross-product eigenvectors of $\check{\mathbf{H}}$. As a consequence, the eigenvectors of $\check{\mathbf{H}}$ and their corresponding eigenvalues remain unchanged, and the rank-two update has now been simplified to the effect solely on the depressed cubic (Eqns. 33 and 39). The system is sufficiently small that direct symbolic examination becomes tractable. The eigenvalues of the rank-two updated matrix are the

roots of:

$$\begin{aligned} \bar{\varepsilon}^3 + c_2\bar{\varepsilon}^2 + c_1\bar{\varepsilon} + c_0 &= 0 \\ c_2 &= -\|\dot{\mathbf{g}}\|_2^2\rho - I_C\eta \\ c_1 &= -(1+2J\rho)I_C - 6J\eta + (\|\dot{\mathbf{g}}\|_2^2 I_C - 9J^2)\rho\eta \\ c_0 &= -(2+3J\rho)J + (I_C^2 - 4\|\dot{\mathbf{g}}\|_2^2)\eta + 2J(I_C^2 - 3\|\dot{\mathbf{g}}\|_2^2)\rho\eta \end{aligned} \quad (42)$$

where η and ρ are defined as:

$$\eta = \frac{2\mu}{(I_C + 1)^2(\lambda(J - 1) - \frac{3}{4}\mu)} \quad \rho = \frac{\lambda}{\lambda(J - 1) - \frac{3}{4}\mu} \quad (43)$$

The cubic is no longer depressed, and while we could apply the cubic formula to obtain a closed-form expression, we found that solving for the roots using the Jenkins and Traub [1970] rpoly algorithm was more practical. The form of the eigenvectors remains the same, $\mathbf{Q}_k = \frac{1}{q_k} \mathbf{U} \mathbf{D}_k \mathbf{V}^T$, but the diagonal entries differ,

$$\mathbf{D}_k = \begin{bmatrix} \alpha_0 & 0 & 0 \\ 0 & \alpha_1 & 0 \\ 0 & 0 & \alpha_2 \end{bmatrix}, \quad (44)$$

and instead take the form:

$$\begin{aligned} \alpha_0 &= \bar{\varepsilon}_k(\sigma_1 + \sigma_0\sigma_2\eta + J\sigma_1\rho) \\ &\quad + \sigma_0\sigma_2 + \sigma_1(\sigma_0^2 - \sigma_1^2 + \sigma_2^2)\eta + J\sigma_0\sigma_2\rho \\ &\quad + \sigma_0(\sigma_0^2 - \sigma_1^2)\sigma_2(\sigma_1^2 - \sigma_2^2)\rho\eta \\ \alpha_1 &= \bar{\varepsilon}_k(\sigma_0 + \sigma_1\sigma_2\eta + J\sigma_0\rho) \\ &\quad + \sigma_1\sigma_2 - \sigma_0(\sigma_0^2 - \sigma_1^2 - \sigma_2^2)\eta + J\sigma_1\sigma_2\rho \\ &\quad - \sigma_1(\sigma_0^2 - \sigma_1^2)\sigma_2(\sigma_0^2 - \sigma_2^2)\rho\eta \\ \alpha_2 &= \bar{\varepsilon}_k^2(\sigma_0^2 + \sigma_1^2)(\eta + \sigma_2^2\rho) \\ &\quad - \sigma_2^2 - 2J\eta - 2J\sigma_2^2\rho + ((\sigma_0^2 - \sigma_1^2)\sigma_2)^2\rho\eta. \end{aligned}$$

Final eigensystem: With these expressions for the rank-two updated system, we can add the $\mu_T = \mu(1 - 1/(I_C + 1))$ regularization term and arrive at the final eigenvalues. The first three are

$$\varepsilon_k = \lambda(J - \alpha)\bar{\varepsilon}_k + \mu_T \quad k = 0 \dots 2 \quad (45)$$

where $\bar{\varepsilon}_k$ are the roots of Eqn. 42. The other six are:

$$\varepsilon_3 = \lambda(J - \alpha)\sigma_0 + \mu_T \quad \varepsilon_6 = -\lambda(J - \alpha)\sigma_0 + \mu_T \quad (46)$$

$$\varepsilon_4 = \lambda(J - \alpha)\sigma_1 + \mu_T \quad \varepsilon_7 = -\lambda(J - \alpha)\sigma_1 + \mu_T \quad (47)$$

$$\varepsilon_5 = \lambda(J - \alpha)\sigma_2 + \mu_T \quad \varepsilon_8 = -\lambda(J - \alpha)\sigma_2 + \mu_T. \quad (48)$$

The first three eigenvectors are specified by Eqns. 39 and 44, and the last six remain the ones described in Appendix A.

5 DISCUSSION AND EXTENSION

In this section, we compare our energy to co-rotational elasticity, and show the generality of our analysis by applying it to Fung and Arruda-Boyce hyperelasticity.

5.1 Co-Rotational as Linearized Neo-Hookean

In §3.2 we described how our energy could be viewed as a singularity-removing Taylor truncation of the original Neo-Hookean energy Ψ_{Neo} . In order to establish a common basis for comparison, we show next how linearizing Ψ_{Neo} yields co-rotational elasticity to within a constant. Starting from the energy in Eqn. 5,

$$\Psi_{\text{Neo}} = \frac{\mu}{2}(I_C - 3) - \mu \log J + \frac{\lambda}{2}(\log J)^2,$$

we can employ the linearization $\log J \approx \text{tr}(\mathbf{S} - \mathbf{I})$ to establish that

$$\begin{aligned} \frac{\mu}{2}(I_C - 3) - \mu \log J &\approx \frac{\mu}{2}\|\mathbf{F} - \mathbf{R}\|_F^2, \\ \frac{\lambda}{2}(\log J)^2 &\approx \frac{\lambda}{2}\text{tr}^2(\mathbf{S} - \mathbf{I}), \end{aligned}$$

and then conclude that (see proof in Appendix C)

$$\Psi_{\text{CR}} = \frac{\mu}{2}\|\mathbf{F} - \mathbf{R}\|_F^2 + \frac{\lambda}{2}\text{tr}^2(\mathbf{S} - \mathbf{I}).$$

Note that Ψ_{CR} contains a $\mu/2$ instead of the μ from Eqn. 3, because the linearization introduces a factor of two that should be accounted for using a Lamé reparameterization similar to §3.4. The constant factor is otherwise irrelevant to our discussion.

5.2 Comparison to Our Energy

From the discussions in §3.2 and §5.1, it is clear that our model applies the approximation $\log J \approx (J - 1)$, while the co-rotational model applies the linearization $\log J \approx \text{tr}(\mathbf{S} - \mathbf{I})$. This is a critical difference, because when the linearization $\text{tr}(\mathbf{S} - \mathbf{I})$ is used, the actual volume $J = \sigma_0\sigma_1\sigma_2$ is no longer computed. Instead, it is assumed that $(\sigma_0\sigma_1\sigma_2 - 1) \approx (\sigma_0 + \sigma_1 + \sigma_2 - 3)$, which only holds for small deformations where $\{\sigma_i\}$ are near 1.

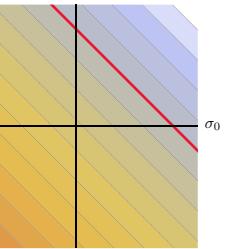
The unacceptable severity of the linearization becomes clear when we visualize its energy in the inset on the right. The volume preservation term $\frac{\lambda}{2}\text{tr}^2(\mathbf{S} - \mathbf{I})$ is minimized when $\text{tr} \Sigma = 3$. The corresponding contour is shown in red and includes inverted configurations, as can be seen when the line strays outside the upper right quadrant. Thus, the energy can report that volume has been perfectly preserved *when in fact elements have been crushed to zero volume or inverted*. The red contour again resembles Fig. 1 from Stomakhin et al. [2012]. In that paper, they propose a “fixed” co-rotational model,

$$\Psi_{\text{FixCR}} = \mu\|\mathbf{F} - \mathbf{R}\|_F^2 + \frac{\lambda}{2}(J - 1)^2. \quad (49)$$

This model is halfway between our model and the original co-rotational model. As with our model, the $\log J \approx (J - 1)$ approximation is applied to the $\frac{\lambda}{2}(\log J)^2$ term, but the problematic linearization $\log J \approx \text{tr}(\mathbf{S} - \mathbf{I})$ is still applied to the $\mu \log J$ term. While Ψ_{FixCR} is stabler than Ψ_{CR} , we show in Fig. 5 that it introduces visual artifacts under large deformation.

Finally, we compare to the St. Venant-Kirchhoff (StVK) energy:

$$\Psi_{\text{StVK}} = \mu\|\mathbf{E}\|_F^2 + \frac{\lambda}{2}\text{tr}^2(\mathbf{E}). \quad (50)$$



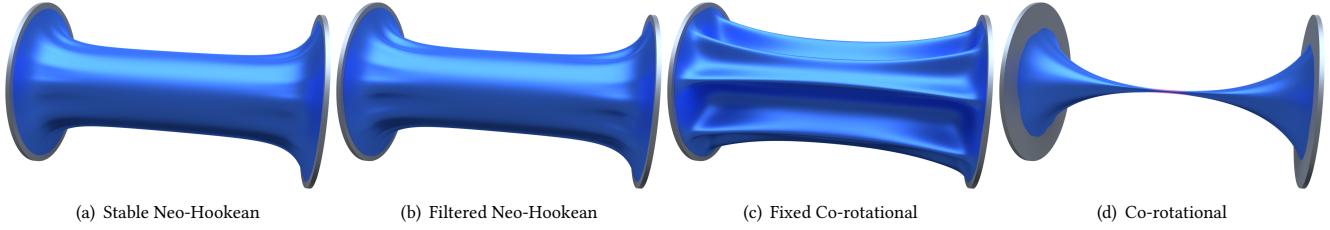


Fig. 5. A cylinder with 306,406 hexahedra and 965,004 degrees of freedom is stretched by a factor of 3.4 with $\nu = 0.49$. The co-rotational model fails entirely, and the “fixed” co-rotational model grows unnatural, sharp fins. Our stable Neo-Hookean model retains the rubber-like appearance of the filtered Neo-Hookean model, exhibits slightly better volume preservation, and does not require any parameter tuning.

Unlike the co-rotational energy, the linear $(\mathbf{F} - \mathbf{R})$ has been replaced with a quadratic Green’s strain $\mathbf{E} = \frac{1}{2}(\mathbf{F}^T \mathbf{F} - \mathbf{I})$. The true volume J is still not computed anywhere, so all of the volume linearization problems from the co-rotational model are present. Irving et al. [2004] observed that this energy contains spuriously stable inverted rest and flattened states, which makes the standard StVK model unattractive for large deformation. Additional compression resistance terms [Kikuuwe et al. 2009] have been proposed:

$$\Psi_{\text{StVK, Kikuuwe}} = \mu \|\mathbf{E}\|_F^2 + \frac{\lambda}{2} \text{tr}^2(\mathbf{E}) + \frac{\kappa}{12} \left(\frac{1-J}{6} \right)^3, \quad (51)$$

where the new term is clamped to zero when $J \geq 1$. While this term helps to preserve volume and remove the spurious stable configurations, it deactivates during extension. The artifacts that arise from the linearized volume term then persist in this regime. We show some of these artifacts in Fig. 10, and include the model in a more extensive version of Fig. 5 in the supplemental material.

5.3 Extension to Other Energies

Our eigenanalysis is sufficiently general that it can be used to analyze any strain energy that employs the I_C and J strain invariants (see §7 for comments on II_C). We have found it straightforward to extend to increased non-linearities in I_C .

General Model: Consider a strain energy density expressed in terms of the I_C and J invariants that leads to a system of the form:

$$\check{\mathbf{A}} = \gamma_I \mathbf{I} + \gamma_F \check{\mathbf{f}}^T + \gamma_G \check{\mathbf{g}}^T + \gamma_H \check{\mathbf{H}}. \quad (52)$$

The eigensystem can be obtained by setting $\eta = \gamma_F/\gamma_H$ and $\rho = \gamma_G/\gamma_H$ in Eqn. 42, and $\mu_T = \gamma_I$ and $\lambda(J-\alpha) = \gamma_H$ in Eqns. 45 through 48. We now examine two specific extensions of our analysis.

Fung Hardening: The exponential hardening of Fung-like models [Fung 2013; Pan et al. 2015; Wang and Yang 2016] is a secondary feature of many biological tissues [Kautzman et al. 2012], so we propose a stabilized Fung model,

$$\Psi_{\text{Fung}} = \frac{\mu_0}{2} (I_C - 3) + \frac{\lambda}{2} (J - \alpha)^2 + \frac{\gamma}{2} \left(e^{\frac{\mu_1}{2}(I_C-3)} - 1 \right), \quad (53)$$

where the rightmost term is the novel one. Following the approach of §3.2, the energy can be stabilized by setting $\alpha = 1 + \frac{\mu_0 + \gamma \mu_1}{\lambda}$. The PK1 then expands to:

$$\mathbf{P}_{\text{Fung}}(\mathbf{F}) = \mu_0 \mathbf{F} + \lambda \frac{\partial J}{\partial \mathbf{F}} (J - \alpha) + \gamma \mu_1 e^{\frac{\mu_1}{2}(I_C-3)} \mathbf{F}. \quad (54)$$

The unfolded, assembled Hessian can then be written as:

$$\check{\mathbf{A}}_{\text{Fung}} = \left(\mu_0 + \gamma \mu_1 e^{\frac{\mu_1}{2}(I_C-3)} \right) \mathbf{I} + \lambda \check{\mathbf{g}} \check{\mathbf{g}}^T + \lambda (J - \alpha) \check{\mathbf{H}} + 2\gamma \mu_1^2 e^{\frac{\mu_1}{2}(I_C-3)} \check{\mathbf{f}} \check{\mathbf{f}}^T. \quad (55)$$

The following constants change in the eigenanalysis:

$$\eta = \frac{2\gamma \mu_1^2 e^{\frac{\mu_1}{2}(I_C-3)}}{\lambda(J-\alpha)} \quad \rho = \frac{1}{J-\alpha} \quad \mu_T = \left(\mu_0 + \gamma \mu_1 e^{\frac{\mu_1}{2}(I_C-3)} \right). \quad (56)$$

Arruda-Boyce: The hardening term can also be represented with a polynomial using the model of Arruda and Boyce [1993]:

$$\Psi_{\text{AB}} = \sum_{i=1}^n a_i (I_C^i - 3^i). \quad (57)$$

We use the three-term expansion for illustrative purposes, shift the constants to maintain consistency with the Neo-Hookean parameters, and arrive at the following energy:

$$\Psi_{\text{AB}} = \frac{\mu}{2} (I_C - 3) + \frac{\mu \beta_1}{4} (I_C^2 - 9) + \frac{\mu \beta_2}{6} (I_C^3 - 27) + \frac{\lambda}{2} (J - \alpha)^2. \quad (58)$$

The energy is rest-stable when $\alpha = 1 + \frac{\mu}{\lambda} (1 + 3\beta_1 + 9\beta_2)$, leading to a PK1 of

$$\mathbf{P}_{\text{AB}}(\mathbf{F}) = \mu \left(1 + \beta_1 I_C + \beta_2 I_C^2 \right) \mathbf{F} + \lambda \frac{\partial J}{\partial \mathbf{F}} (J - \alpha) \quad (59)$$

and a Hessian of

$$\check{\mathbf{A}}_{\text{AB}} = \mu \left(1 + \beta_1 I_C + \beta_2 I_C^2 \right) \mathbf{I} + \lambda \check{\mathbf{g}} \check{\mathbf{g}}^T + \lambda (J - \alpha) \check{\mathbf{H}} + 2\mu (\beta_1 + 2\beta_2 I_C) \check{\mathbf{f}} \check{\mathbf{f}}^T. \quad (60)$$

This system leads to the following constants in the eigenanalysis:

$$\eta = \frac{2\mu(\beta_1 + 2\beta_2 I_C)}{\lambda(J-\alpha)} \quad \rho = \frac{1}{J-\alpha} \quad \mu_T = \mu \left(1 + \beta_1 I_C + \beta_2 I_C^2 \right). \quad (61)$$

6 RESULTS

We evaluate the robustness of our model across a variety of scenarios. All quasistatic examples use a (potentially non-manifold [Mitchell et al. 2015]) hexahedral mesh with eight-point quadrature. To show the agnosticism of our energy to topology and integration scheme, we also include a dynamic example using linear tetrahedra. Quasistatic simulations are performed with a standard Newton solver augmented with a line search, and linear systems are solved using ViennaCL’s Conjugate Gradient implementation running on OpenCL [Rupp et al. 2010]. All Newton solves were run until the

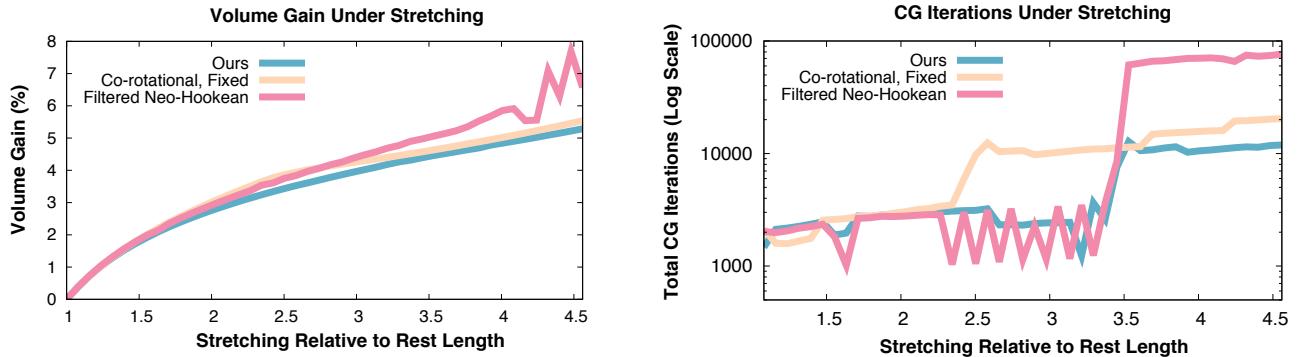


Fig. 6. In the left graph, our model exhibits the best volume preservation under stretching. In the right graph, our CG iteration count is competitive with the other models, and under large stretches, our model consistently converges faster. Our model took an average of 100.64s per frame, filtered Neo-Hookean took 537.72s, and “fixed” co-rotational took 144.07s.

absolute L_2 -norm of the force residual was less than $1e^{-2}$. After normalizing by the number of degrees of freedom, we are essentially solving to single precision. All simulations were performed with a 2.3 GHz Intel Xeon E5-2699 on 8 cores, 118 GB of RAM, and an NVIDIA Quadro M6000 GPU.

Stretch Test. We stretch a cylinder composed of 306,406 hexahedra to 3.4 times its original length by translating hard-constrained vertices on two opposing faces. We compare to three models:

- The co-rotational energy Ψ_{CR} from Irving et al. [2004]
- The “fixed” co-rotational Ψ_{FixCR} of Stomakhin et al. [2012]
- The original Neo-Hookean energy Ψ_{Neo} , but “filtered” using Teran et al. [2005].

In all cases, we call the original implementations in the PhysBAM codebase [Dubey et al. 2011], which one of the original authors has generously provided for us. The default force filtering threshold $\sigma_f = 0.25$ and Hessian projection threshold $\epsilon_p = -1e^{-4}$ from the code were used. We show results for an extreme Poisson’s ratio of $\nu = 0.49$ in Fig. 5. A wide range of additional ν , as well as comparisons to the C_2 model from Stomakhin et al. [2012] and the StVK model from Kikuuwe et al. [2009], are shown in the supplemental materials.

We first examine volume preservation. In Fig. 6, the co-rotational model loses over 83.0% of the original volume; linearizing the volume penalty is clearly inadequate for this case. The “fixed” co-rotational model only gains 4.5% volume, but the final shape contains highly unnatural crinkling. An analogous artifact is shown in Fig. 6 of Stomakhin et al. [2012], and our analysis suggests that it stems from the linearization hidden in the $\frac{\mu}{2} \|\mathbf{F} - \mathbf{R}\|_F^2$ term. Filtered Neo-Hookean gains 4.9% volume, slightly more than the other model. Finally, our stable Neo-Hookean model gains 4.3% volume, which is the smallest of any of the models.

In order to compare computational performance, we use the total number of conjugate gradient (CG) iterations performed by the Newton solver at each time step. This is more instructive than the total Newton iterations in this case, because many of the solves in Fig. 5 completed in fewer than 3 iterations. It also removes constant

factors associated with low-level optimization that has been applied to various components of the code, e.g. the PhysBAM classes.

The “fixed” co-rotational model requires the most CG iterations, roughly 2.3 times the total CG iterations of our model for the stretch in Figure 5. This may be because at larger deformations, the inconsistent approximations applied to the $\log J$ term begin to conflict. On average, our stable Neo-Hookean model takes slightly more CG iterations than filtered Neo-Hookean, with 1.2 times the total CG iterations; the computational costs are virtually identical. Our model contains none of the artifacts from the “fixed” co-rotational model, and preserves volume better than the filtered Neo-Hookean model.

The CG iteration counts for the original co-rotational model are not shown because they are an order of magnitude larger than the other models. Converging to the degenerate geometry in Fig. 5 is computationally expensive. We also attempted to simulate the C_2 continuous Neo-Hookean model from Stomakhin et al. [2012]. While the model converged fine for lower ν (see supplemental materials), we were unable to locate settings that did not diverge before completing the test for $\nu = 0.49$.

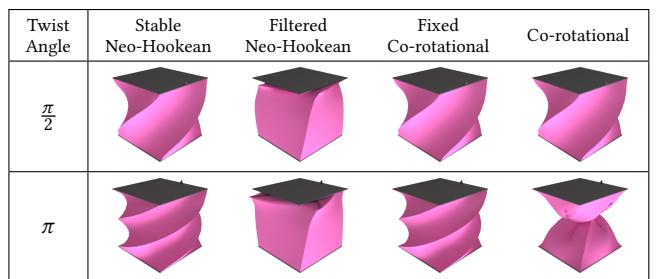


Fig. 9. The top face of the cube undergoes two successive $\pi/2$ rotations. Stable Neo-Hookean and “Fixed” Co-rotational resolve the twist robustly. Co-rotational has trouble with the second rotation, and filtered Neo-Hookean is unable to resolve the shape. The cube is discretized with 15^3 hexahedral elements and the material models are simulated with $\nu = 0.49$.

Twist Test: We take a unit cube and subject it to large kinematic rotations by hard-constraining one face of the cube and rotating it

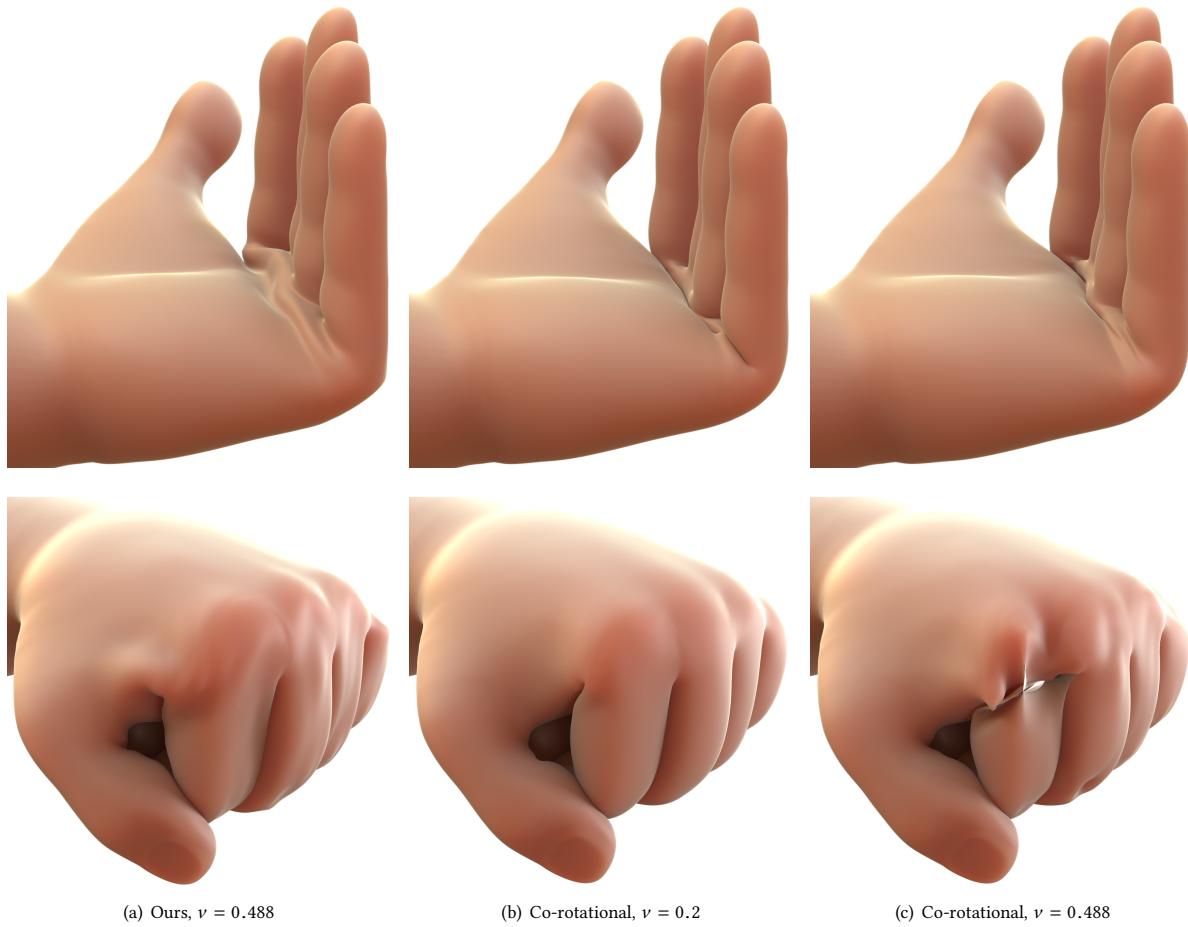


Fig. 7. Top: Our model captures the bulge in the palm at the base of the fingers. **Bottom:** Our model captures the bulge in the webbing between the pointer finger and the thumb. At $v = 0.2$, Co-rotational elasticity resembles contact-aware skinning. Increasing to $v = 0.488$ only introduces artifacts and fails to capture the features of our model. The simulation is driven by 24 kinematic bones in the hand and the forearm, and the mesh consists of 41,050 hexahedra and 142,995 degrees of freedom. Stable Neo-Hookean took an average of 15.9 Newton iterations, 9,486.7 CG iterations, and 53.8 seconds. With Co-rotational at $v = 0.2$, the average is 13.1 Newton iterations, 2,471.9 CG iterations, and 44.0 seconds. With Co-rotational at $v = 0.488$, the simulation did not complete. ©Disney/Pixar

twice by $\pi/2$ radians. Production quasistatic flesh simulations often undergo rotations of this magnitude, so it is critical that models remain robust under these conditions. The cube is discretized into 15^3 hexahedra, and $v = 0.49$. Our model finds the correct twisted shape, where the solves respectively took 12 and 16 Newton iterations, and 3,278 and 4,956 CG iterations (Fig. 9).

The “fixed” co-rotational model is also able to robustly resolve both rotations in 11 and 15 Newton iterations and 2,940 and 4,348 CG iterations. The co-rotational model resolves the $\pi/2$ rotation, but then collapses. For the π rotation, 223 Newton iterations were needed; resolving collapsed configurations is again costly. Collisions were disabled, so the results involve purely the material model. Filtered Neo-Hookean yields unusable results. The solve stalls when the line search is enabled, and diverges when it is disabled.

Scramble. In Fig. 3 we perform a “scramble” test similar to those in Teran et al. [2005] and Stomakin et al. [2012] by randomly placing the vertices of a unit cube within a cube of twice the rest volume. To separate the behavior of our model from that of mass-regularization, we perform a quasistatic solve. We pin four cube corners in order to constrain the rigid modes. As shown in the supplemental video, our model successfully recovers the rest pose.

Torso. In Fig. 1, we perform a quasistatic flesh simulation of arms and a torso that are driven kinematically by a set of internal bones. The bones are transformed by the skinning of a production rig, which often results in non-rigid transforms and intersecting bones. Like the co-rotational model, our model is robust to these noisy inputs. However, our model produces realistic bulges and folds, while the co-rotational model produces artifacts and collapses the shoulder entirely. Increasing v only worsens the artifact; the

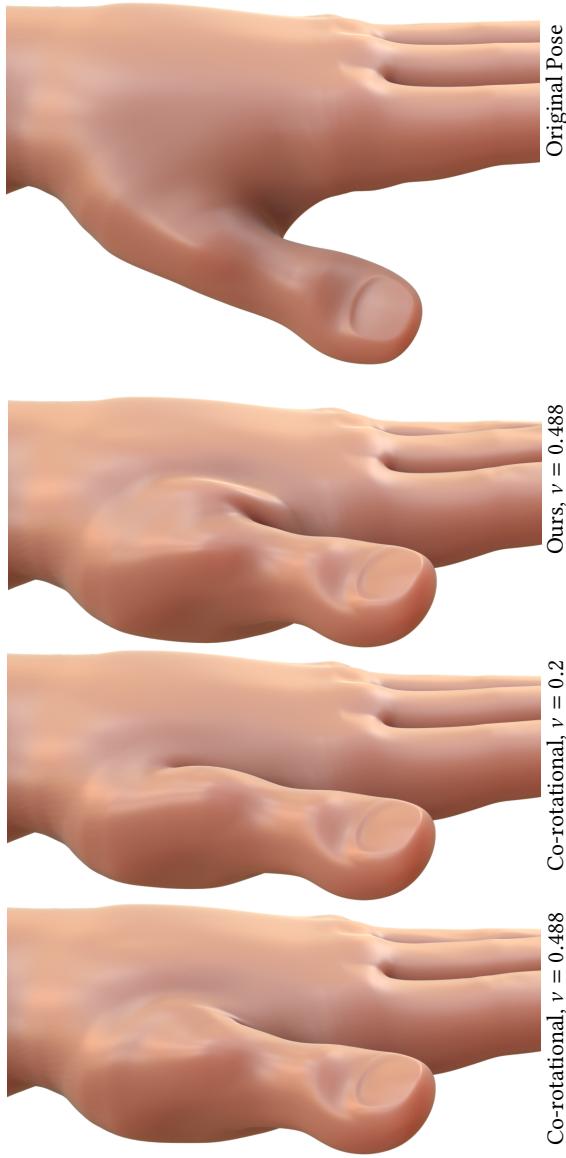


Fig. 8. **Top:** The thumb at its original rest pose. **Top, middle:** When pinched, the flesh between the thumb and pointer bulges with our model set to $v = 0.488$. **Bottom, middle:** With the Co-rotational model, there is no feature at $v = 0.2$. **Bottom:** Only slight bulging appears in the Co-rotational model at $v = 0.488$. The settings and timings are the same as Fig. 7. ©Disney/Pixar

parameter accomplishes the opposite of its stated purpose. In Fig. 10, we compare our model to an StVK model with a compression resistance term [Kikuuwe et al. 2009]. The StVK model fails to capture the fleshy profile of our model.

Collisions are enabled in this simulation, and handled with a reference map-based penalty force [Hirota et al. 2001; Irving et al. 2004]. Starting from a surface point sampling, a spatial grid acceleration structure [McAdams et al. 2011] is used to locate sample points in a



Fig. 10. Left: A bicep under an imposed elbow flexion simulated with our stable Neo-Hookean model ($v = 0.488$). An average time step took 13.7 Newton iterations, 5,860 Conjugate Gradient (CG) iterations, and 25.6 seconds. **Right:** The same pose with StVK and a compression resistance term ($v = 0.488$, $\kappa = 8 \times 10^8$). The StVK model fails to capture the fleshy silhouette we observe with our model, and instead leaves a gap between the bicep and forearm. An average time step with this model took 32 Newton iterations, 14,446 CG iterations, and 140.3 seconds. ©Disney/Pixar

tetrahedralization of the hexahedral mesh. If a sample point collides with a tetrahedron, it is mapped to the reference domain, where the closest surface point is computed. The surface point and the original surface sample are mapped back to the deformed domain, and define a penalty spring. Due to the two linear maps, this target position is not always the closest point on the deformed surface mesh. If clean and conforming contacts are desired, an additional local optimization is performed on the deformed surface mesh that iteratively searches for closer points. This process typically converges in a single iteration.

Hand. In Figs. 7 and 8, we simulate the flesh on a hand and forearm. As with the torso, bones drive the simulation, but their transforms come from a skinning that is noisy, and contains difficult stretches and intersections. Similar to McAdams et al. [2011], the simulation both cleans up skinning artifacts around difficult joints, and adds physics-based details that were missing in the original rig.

The co-rotational model consistently collapses regions where volume should be preserved, such as wrinkles in the palm of the hand, or folds in the webbing between the thumb and pointer finger. As with the torso example, increasing v can worsen artifacts, and in some cases causes the Newton solve to diverge.

Dynamics. In Fig. 11, we show our material model undergoing dynamic, extreme collisions. Despite the majority of the model being squashed to almost zero volume, our elastic energy allows it to recover. The simulation uses a tetrahedral mesh, and shows that our model is agnostic to element type and quadrature scheme.

7 CONCLUSIONS AND FUTURE WORK

We have designed a new hyperelastic energy that requires no special machinery to remain stable under large deformations, including inversions. We are able to derive closed-form expressions for the

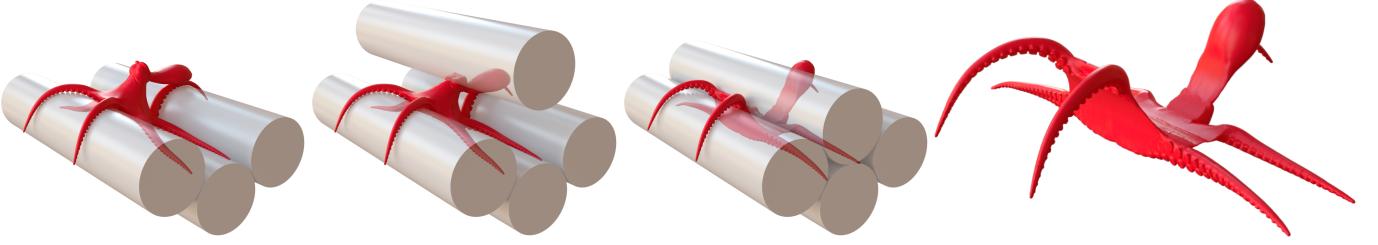


Fig. 11. We dynamically drop an octopus containing 394,268 tetrahedra and 278,991 degrees of freedom with $v = 0.46$ onto three cylinders. We squash it with another cylinder, but it recovers as soon as the cylinder is removed. For clarity, the cylinders are visualized with partial transparency. On the right is a close-up of the most squashed state. The simulation took 10 semi-implicit [Baraff and Witkin 1998] substeps per frame to resolve the collisions, and each frame took an average of 20.8 seconds. ©Disney/Pixar

eigendecompositions of all its components. The sum of these components also possesses a special structure that allow us to write simple expressions for its eigensystem. Together, these findings allow our energy to be used in Newton-based implicit schemes that use conjugate gradient solvers.

We have established a hierarchy of Neo-Hookean approximations. The co-rotational elasticity model is the simplest, as it applies the $\log J \approx \text{tr}(\mathbf{S} - \mathbf{I})$ linearization to both Neo-Hookean terms, followed by the model of Stomakhin et al. [2012], which only applies it to one. Our energy instead consistently uses $\log J \approx (J - 1)$ everywhere. This critical difference allows volume to be measured accurately under large deformation, and improves both the stability and quality of the simulation. The $\log J \approx (J - 1)$ approximation is a first-order truncation, so one direction for future work is to determine the benefits of higher-order truncations.

In §4, we performed a complete eigenanalysis of the first stress invariant I_C and the volume measure J . Our analysis of J also constitutes an analysis of the third stress invariant, $III_C = J^2$. These results can be used to analyze *any* energy that can be written in terms of I_C and III_C , as we show with the Fung and Arruda-Boyce models in §5.3. An eigenanalysis of the second invariant, $II_C = \text{tr}(\mathbf{C}^T \mathbf{C})$, is still missing, and could lead to a better understanding of materials such as the Mooney-Rivlin and Verdon models.

Finally, a better understanding of how Hessian indefiniteness impacts Newton convergence is needed. Allowing a slight amount of indefiniteness to enter into the global Hessian can sometimes accelerate Newton convergence, so a better understanding of this phenomenon could yield significant practical benefits.

ACKNOWLEDGEMENTS

We would like to thank David Eberle and Audrey Wong for their last-minute help getting the tetrahedral octopus simulation from Fig. 11 pushed through Presto and Fizt. We would also like to thank Jonathan Page for providing both the bone geometry and finger animation in Fig. 7, Bill Wise for providing the geometry and animation for the torso example in Fig. 1, and Rick Sayre for approving the use of the torso asset. Thanks also to Tony DeRose and Doug James for their feedback on early drafts of this work.

A VOLUME HESSIAN EIGENVECTORS

The first three eigenvectors, $\varepsilon_{0\dots 2}$, are specified by Eqns. 39 and 40. The remaining six, $\varepsilon_{3\dots 8}$, are of the form:

$$\mathbf{Q}_k = \frac{1}{\sqrt{2}} \mathbf{U} \mathbf{D}_k \mathbf{V}^T. \quad (62)$$

The only differences are in the \mathbf{D}_i matrices, which are:

$$\begin{aligned} \mathbf{D}_3 &= \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & -1 & 0 \end{bmatrix} & \mathbf{D}_6 &= \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \\ \mathbf{D}_4 &= \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ -1 & 0 & 0 \end{bmatrix} & \mathbf{D}_7 &= \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix} \\ \mathbf{D}_5 &= \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} & \mathbf{D}_8 &= \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \end{aligned}$$

B ORTHOGONALITY TO PSEUDO-CROSS-PRODUCTS

THEOREM B.1. If $\mathbf{B} \in \mathbb{R}^{3 \times 3}$ can be diagonalized using the \mathbf{U} and \mathbf{V} from \mathbf{F} , then $\text{vec}(\mathbf{B}) = \check{\mathbf{b}}$ is orthogonal to all six pseudo-cross-product eigenvectors in Eqn. 62.

Proof: We denote the eigenvectors in flattened form as $\text{vec}(\mathbf{Q}_k) = \check{\mathbf{q}}_k$. If we can show that $\check{\mathbf{q}}_k^T \check{\mathbf{b}} = 0$, then we are done. First, we observe that $\check{\mathbf{q}}_k^T \check{\mathbf{b}} = \text{tr}(\mathbf{Q}_k^T \mathbf{B})$. Next, we use the assumption that \mathbf{B} can be diagonalized: $\mathbf{B} = \mathbf{U} \Sigma_B \mathbf{V}^T$. Since $\mathbf{Q}_k = \mathbf{U} \mathbf{D}_k \mathbf{V}^T$, we have $\text{tr}(\mathbf{Q}_k^T \mathbf{B}) = \text{tr}(\mathbf{D}_k^T \Sigma_B) = 0$. Finally, we observe that \mathbf{D}_k are *hollow* matrices, i.e. they are zero along their diagonals. The trace of a diagonal times a hollow matrix is zero. Thus, $\check{\mathbf{q}}_k^T \check{\mathbf{b}} \equiv \text{tr}(\mathbf{Q}_k^T \mathbf{B}) \equiv \text{tr}(\mathbf{D}_k^T \Sigma_B) = 0$. \square

COROLLARY B.2. The vector $\check{\mathbf{g}}$ is orthogonal to all six pseudo-cross-product eigenvectors.

Proof: The vector $\check{\mathbf{g}}$ is generated from the matrix $\frac{\partial J}{\partial \mathbf{F}}$, i.e. $\text{vec}\left(\frac{\partial J}{\partial \mathbf{F}}\right) = \check{\mathbf{g}}$. This matrix can be diagonalized as

$$\frac{\partial J}{\partial \mathbf{F}} = \mathbf{U} \begin{bmatrix} \sigma_1 \sigma_2 & 0 & 0 \\ 0 & \sigma_0 \sigma_2 & 0 \\ 0 & 0 & \sigma_0 \sigma_1 \end{bmatrix} \mathbf{V}^T. \quad (63)$$

By the preceding theorem, $\check{\mathbf{g}}$ is orthogonal. \square

C CO-ROTATIONAL AS LINEARIZED NEO-HOOKEAN

LEMMA C.1. $\text{tr}(\mathbf{S} - \mathbf{I})$ is a linearization of $\log J$.

Proof: Given the polar decomposition $\mathbf{F} = \mathbf{R}\mathbf{S}$ (Table 1), we have $J = \det \mathbf{F} = \det \mathbf{S}$. By applying the identity $\det \mathbf{S} = e^{\text{tr}(\log \mathbf{S})}$, we obtain $\log J = \text{tr}(\log \mathbf{S})$. We then compute the Taylor expansion about $\mathbf{S} = \mathbf{I}$

$$\log \mathbf{S} = (\mathbf{S} - \mathbf{I}) - \frac{1}{2}(\mathbf{S} - \mathbf{I})^2 + \frac{1}{3}(\mathbf{S} - \mathbf{I})^3 \dots, \quad (64)$$

and employ its linear term to conclude: $\log J \approx \text{tr}(\mathbf{S} - \mathbf{I})$. \square

THEOREM C.2. $\mu/2\|\mathbf{F} - \mathbf{R}\|_F^2$ is a linearization of $\mu/2(I_C - 3) - \mu \log J$.

Proof: This follows from an algebraic manipulation:

$$\begin{aligned} \frac{\mu}{2}(I_C - 3) - \mu \log J &= \frac{\mu}{2}(\|\mathbf{F}\|_F^2 - \text{tr} \mathbf{I}) - \mu \log J \\ (\text{applying Lemma C.1}) &\approx \frac{\mu}{2}(\|\mathbf{F}\|_F^2 - \text{tr} \mathbf{I}) - \mu \text{tr}(\mathbf{S} - \mathbf{I}) \\ &= \frac{\mu}{2}(\|\mathbf{F}\|_F^2 + \text{tr} \mathbf{I} - 2 \text{tr} \mathbf{S}) \\ &= \frac{\mu}{2}(\|\mathbf{F}\|_F^2 + \|\mathbf{R}\|_F^2 - 2 \text{tr}(\mathbf{R}^T \mathbf{F})) \\ &= \frac{\mu}{2}\|\mathbf{F} - \mathbf{R}\|_F^2. \end{aligned}$$

Therefore: $\frac{\mu}{2}(I_C - 3) - \mu \log J \approx \frac{\mu}{2}\|\mathbf{F} - \mathbf{R}\|_F^2$. \square

COROLLARY C.3. $\lambda/2 \text{tr}^2(\mathbf{S} - \mathbf{I})$ is a linearization of $\lambda/2(\log J)^2$.

Proof: We can reuse Lemma C.1 and the linearization appears immediately. \square

D EIGENSYSTEM WHEN $\nu \geq 0.4$

If fleshy material with $\nu \geq 0.4$ is being simulated, the regularized origin barrier can be discarded, and the simpler eigensystem from that results from Eqn. 13 can be used instead. The Hessian is then,

$$\ddot{\mathbf{A}} = \mu \mathbf{I} + \lambda \ddot{\mathbf{g}} \ddot{\mathbf{g}}^T + \lambda(J - \alpha) \ddot{\mathbf{H}}, \quad (65)$$

which is only a rank-one updated system. The deflation argument from §4.6 still applies, and the rank-one updated cubic is instead

$$\bar{\varepsilon}^3 - \rho \|\ddot{\mathbf{g}}\|_2^2 \bar{\varepsilon}^2 - (1 + 2\rho J)\|\mathbf{F}\|_F^2 \bar{\varepsilon} - (2 + 3\rho J)J = 0, \quad (66)$$

where $\rho = (J - \alpha)^{-1}$. The diagonal entries in the eigenvector $\mathbf{Q}_k = \frac{1}{q_k} \mathbf{U} \mathbf{D}_k \mathbf{V}^T$ can be written as:

$$\mathbf{D}_k = \begin{bmatrix} \alpha(\sigma_0\sigma_2 + \sigma_1\bar{\varepsilon}_k) & 0 & 0 \\ 0 & \alpha(\sigma_1\sigma_2 + \sigma_0\bar{\varepsilon}_k) & 0 \\ 0 & 0 & \bar{\varepsilon}_k^2 - \beta\sigma_2^2 \end{bmatrix} \quad (67)$$

$$\alpha = 1 + \rho J$$

$$\beta = \alpha + \rho(J + (\sigma_0^2 + \sigma_1^2)\bar{\varepsilon}_i).$$

Note that for the case of $\rho = 0$, Eqn. 40 is recovered. The final eigenvalues are now the same as in Eqns. 45 - 48, except that the roots of Eqn. 66 are used instead, and $\mu_T = \mu$.

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