

# RIPS 2009 Disney/Pixar Project Description

## Parameter Estimation for Constitutive Models of Deformable Objects

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### 1 Summary

Physics based simulations are frequently used to model the behavior of deformable objects in 3D animations. Whether the goal is achieving physically realistic or artistically styled behavior, a number of parameters must be tuned for each model. Parameter determination can be unintuitive, especially in more complicated models, so an automated procedure is desired.

### 2 Background

The general problem can be formulated as follows:

Given target data  $x^t$  and a parametric constitutive model, determine the set of material and other environmental parameters  $\lambda$  which best fit the simulated data  $x(\lambda)$  to  $x^t$ .

It can be applied to a wide range of applications from determining material properties of biological tissues to creating realistic objects for interactive virtual environments, so many constitutive models, target data types, and solution techniques have been explored depending on the focus of the application. Biomedical models typically focus on local properties of tissue samples [5, 4, 2]. The constitutive models can be complex, (non-linear, anisotropic, viscoelastic); however, they are only interested local behavior, so simplifying assumptions such as axial symmetry and homogeneity are frequently invoked. On the other side, a number of computer graphics applications are interested in large heterogeneous objects [6, 3]. However, fast computations are often desired, so the constitutive models are usually linear.

In many cases, the best fit parameters are computed via a gradient method (such as Gauss-Newton) [7, 5, 4]; however, due to the ill-posedness of many inverse problems, gradient methods are frequently unable to find global minima without further reformulation and other special considerations. As such, other more global methods such as particle filtering [1] and response surfaces [2] have been used.

### 3 Relevance to animation

In the animated film and visual effects industries, character deformation is typically accomplished using procedural character “rigs.” These map a set of animation controls to a geometric surface deformation representing a character. The strength of character rigs is their frame independence and procedural nature, making them easy to evaluate and change (no simulation is required). Unfortunately, they have difficulty deforming the character to adhere to environmental constraints (e.g. contact and collision with other objects) and lack inertial effects (jiggling or motion follow through). Finite element methods for driving deformation can capture the missing effects but are difficult to control and more computationally expensive, preventing their widespread use in character work.

A robust parameter estimation framework will ease the difficulties with finite elements. In particular, it will allow a user to create a character design (in the form of a rig) and find a parameterized constitutive model

that can match the rig while at the same time be able to work in much more general situations. Obviously, such a constitutive model would have different and many more controls than most standard constitutive models to be able to match an input rig. Nevertheless, this would not only remove the burden of choosing parameters for the finite element model but also allow the more computationally expensive model to be used only where it is needed, because the two models will match in simpler cases.

## 4 Project Objectives

We will be using PhysBAM, a physics-based simulation C++ library, for this project. Deformable object simulation with a number of constitutive models is already supported, so our goal will be to develop an algorithm which will fit this simulation output to target data. As the difficulty of the problem depends on the complexity of the chosen constitutive model, a tiered approach where the problem is solved for models of increasing complexity is suggested. A precedent for parameter estimation via Gauss-Newton and similar minimization techniques exists in PhysBAM [7], so this would be the simplest method to implement first.

### 4.1 Target data and Constitutive Model Selection

Our target data will be 3D animated objects. Although we would like to develop a system which will work for a wide range of animated objects, an initial goal will be homogeneous quasistatic linear elastic materials. The addition of non-linearity or heterogeneity would be a useful second step. Nearly incompressible materials (e.g. those with a high water content) are of interest, and special handling of stiff “volume-preserving” terms may be needed. Additionally, nearly all inverse constitutive model problems assume a quasistatic model (i.e. the inertial forces are negligible). While this simplifies the model, there are many jiggly objects in animation which cannot be accurately handled with a quasistatic assumption.

### 4.2 Parameter Estimation

The Gauss-Newton method applied to this problem can be defined as follows. For a given constitutive model, let  $\lambda$  be a vector of the unknown material parameters and  $x(\lambda)$  be the spatial configuration of the simulated body. Additionally, define  $x^t$  as the target spatial configuration. Then we can determine the set of parameters which optimally approximate this configuration as the solution to the minimization problem

$$\lambda_{opt} = \arg \min_{\lambda} E(\lambda), \text{ where } E(\lambda) = \|x(\lambda) - x^t\|^2$$

A quadratic approximation to  $E$  would then be

$$E(\lambda) \approx \|x(\lambda_k) + \frac{\partial x(\lambda_k)}{\partial \lambda} d\lambda - x^t\|^2$$

which suggests an iterative optimization scheme  $\lambda_{k+1} = \lambda_k + d\lambda$ , where  $d\lambda$  is the least squares solution to the linear system

$$-\frac{\partial x(\lambda_k)}{\partial \lambda} d\lambda = x(\lambda_k) - x^t.$$

Since the function  $x(\lambda)$  is usually not known, further assumptions and work must be done to determine  $\frac{\partial x(\lambda)}{\partial \lambda}$ . This approach applied to a similar problem can be found in [7].

## 5 Project Deliverables

1. Software (PhysBAM code)
2. Experimental results (videos)
3. A written report outlining methods used and results
4. A presentation

## References

- [1] S. Burion, F. Conti, A. Petrovskaya, C. Baur, and O. Khatib. Identifying physical properties of deformable objects by using particle filters. *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on*, pages 1112–1117, May 2008.
- [2] Daniell Einstein, Alan Freed, Nielen Stander, Bahar Fata, and Ivan Vesely. Inverse parameter fitting of biological tissues: A response surface approach. *Annals of Biomedical Engineering*, 33(12):1819 – 1830, 2005.
- [3] M. Hauth, J. Gross, and W. Strasser. Interactive physically based solid dynamics. In *SCA '03: Proceedings of the 2003 ACM SIGGRAPH/Eurographics symposium on Computer animation*, pages 17–27, Aire-la-Ville, Switzerland, Switzerland, 2003. Eurographics Association.
- [4] M. Kauer, V. Vuskovic, J. Dual, G. Szekely, and M. Bajka. Inverse finite element characterization of soft tissues. *Medical Image Analysis*, 6(3):275 – 287, 2002.
- [5] Michael J. Moulton, Lawrence L. Creswell, Ricardo L. Actis, Kent W. Myers, Michael W. Vannier, Barna A. Szabo, and Michael K. Pasque. An inverse approach to determining myocardial material properties. *Journal of Biomechanics*, 28(8):935 – 948, 1995.
- [6] Dinesh K. Pai, Kees van den Doel, Doug L. James, Jochen Lang, John E. Lloyd, Joshua L. Richmond, and Som H. Yau. Scanning physical interaction behavior of 3d objects. In *SIGGRAPH '01: Proceedings of the 28th annual conference on Computer graphics and interactive techniques*, pages 87–96, New York, NY, USA, 2001. ACM.
- [7] Eftychios Sifakis, Igor Neverov, and Ronald Fedkiw. Automatic determination of facial muscle activations from sparse motion capture marker data. *ACM Trans. Graph.*, 24(3):417–425, 2005.